Technological Forecasting & Social Change 158 (2020) 120155

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Geographic distance, venture capital and technological performance: Evidence from Chinese enterprises

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ARTICLE INFO

Keywords:
Geographic distance
Venture capital (VC)
Technological performance
Equity background
Investment strategy
Nonlinear effect

ABSTRACT

Venture capital (VC) plays an increasingly important role in advancing the technological innovation of enterprises. A growing body of evidence suggests that VC influences the technological performance of enterprises. No known empirical studies have focused on the relationships between geographic distance and the enterprise's technological performance. This study explores whether and how the geographic distance between VC institutions and enterprises influences the enterprise's technological performance from the perspective of the VC's equity backgrounds (governmental, private, and foreign) and investment strategies (independent and joint). The findings and conclusions are as follows: (1) The geographic distance between VC institutions and enterprises has a significantly nonlinear effect on the technological performance of the VC-backed enterprise, and they are negatively correlated when the geographic distance is less than the specified threshold. (2) The influence of geographic distance on the enterprise's technological performance varies with the VC's equity backgrounds. Geographic distance has a more significant impact on the technological performance of governmental VC- and private VC-backed enterprise compared with foreign VC-backed enterprise. (3) For different investment strategies, geographic distance also has a distinct influence on the enterprise's technological performance. When compared with joint VC, the impact of independent VC on the enterprise's technological performance is more influenced by geographic distance.

1. Introduction

"Mass entrepreneurship and innovation" is a vital engine of economic development, and it serves as an essential symbol that China's economy has entered a new normal. However, entrepreneurship and innovation cannot do without the support of venture capital (VC) (Kortum and Lerner, 2000; Reichardt and Weber, 2006; Zhang et al., 2018; Kaminski et al., 2019; Yu et al., 2020). Because VC can provide financial support and a relationship network (Bottazzi et al., 2008; Jin et al., 2016; Coccia, 2019; Xue et al., 2019) for small and medium-sized enterprises (SMEs) to overcome the innovation difficulties faced by them, and improve their technological performance. VC stimulates the innovation of SMEs through activities such as alleviating information asymmetry, providing financing, and strengthening governance (Kortum and Lerner, 2000; Coccia, 2017a). Therefore, VC plays an essential role in promoting the development of SMEs and emerging industries. In recent years, the government has issued a series of policies and measures to optimize the development environment for VC in China.

VC has developed rapidly in response to the support of national policy in China (See Fig. 1). In Fig. 1, the VC market has experienced slow and steady growth since the 1990s. But since 2013, the number and investment amount of VC events have exploded. The number of VC events increased from 1337 in 2013 to 6007 in 2018, and the amount of investment increased from 92 billion RMB in 2013 to 1267 billion RMB in 2018. However, there are some fluctuations in the growth process. For example, the number of VC events declined in 2008 because of the global financial crisis. Nevertheless, it rose slightly in 2009 owing to the launch of the growth enterprise market. Moreover, the investment amount of VC events fell rapidly in 2012 and 2013 due to the influence of the European and US debt crisis, while it has exploded year by year for support by China's investment policies after 2013.

VC institutions are geographically clustered (Chen et al., 2010), with primary concentrations in developed cities in China, including Beijing, Shanghai, Shenzhen, and Guangzhou, while there are few VC institutions in the central and western regions (Long and Li, 2016). The spatial agglomeration of VC further increases regional differences in China. For example, in 2018, Beijing, Shanghai, and Guangdong are the

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https://doi.org/10.1016/j.techfore.2020.120155
Received 9 August 2019; Received in revised form 16 March 2020; Accepted 6 June 2020
Available online 27 June 2020
0040-1625/

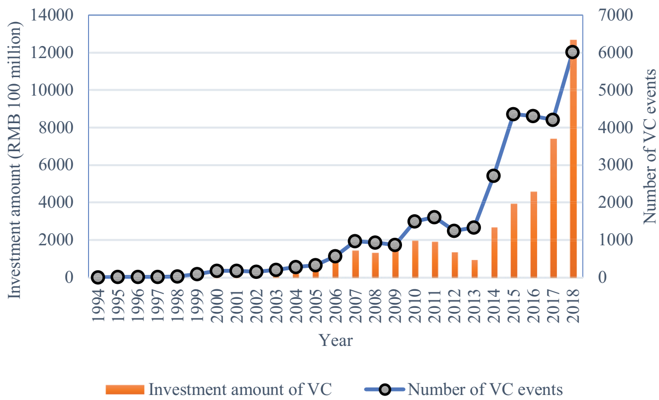

Fig. 1. The number and investment amount of VC events in China (1994–2018).
Data source: Wind Database, https://www.wind.com.cn.

main destinations of VC institutions, with investments reaching 384.40 billion RMB, 178.04 billion RMB, and 118.69 billion RMB, respectively, and with the number of investment events counting of 1697, 977, and 890, respectively.[1] The three regions account for more than half number of all the VC institutions in China. The unbalanced distribution of VC institutions may further aggravate the imbalance of current regional development, and thus affects the improvement of innovation capability.

However, as the geographic distance between VC institutions and enterprises increases, the supervision and management of VC institutions to enterprises will decrease, and accordingly, the risks for VC institutions increase. Because of this, VC institutions may prefer to invest the enterprises that are close to them, making it harder for enterprises with a long geographic distance to obtain their investments (Belderbos et al., 2018). More importantly, geographic proximity can promote the exchange of information between VC institutions and enterprises, and also can reduce the transaction and oversight costs of investment activities (Cumming and Dai, 2010).

Due to the geographic proximity of VC activities, it is necessary to analyze the impact of VC on the technological performance of enterprises from the perspective of geography distance. First, the geographic distance between VC institutions and enterprises is a crucial decision variable for decision-makers (Boschma, 2005; Dushnitsky and Lenox, 2005; Maggioni and Uberti, 2009; Cumming and Dai, 2010). Second, the asymmetric information is more significant as the geographic distance increases (Ivkovic and Weisbenner, 2005; Karlsson, 2010; Chen et al., 2011; Tian, 2011; Kolympiris et al., 2018), since VC institutions are sticky and difficult to change as the distance increases (Grilli et al., 1994). Third, geographic proximity is beneficial for VC institutions to guide, supervise and manage enterprises, thus reducing transaction costs, and it also affects enterprise's financial and technological performance (Wadhwa and Kotha, 2006; Keil et al., 2008; Zahra and Hayton, 2008; Van et al., 2011; Hoenen et al., 2014; Bengtsson and Ravid, 2015; Hochberg et al., 2015; Belderbos et al., 2018).

In this study, we analyze whether and how the geographic distance between VC institutions and enterprises affects the technological performance of VC-backed enterprise. The contributions of this study are given as follows: (1) We explore the effect of geographic distance on the technological performance of VC-backed enterprise from the heterogeneity of VC's equity backgrounds (e.g., governmental, private, and foreign). (2) We consider the heterogeneity of VC investment strategies, such as joint investment and independent investment, and we also provide the empirical evidence for the impact of geographic distance on the technological performance of enterprise supported by VC. (3) We not only examine the linear effect of geographic distance between VC institutions and enterprises on the enterprise's technological performance, but also analyze its nonlinear effect using the panel threshold model.

The rest of this paper is organized as follows: Section 2 explores the theoretical analysis and research hypothesis. Section 3 describes the research design, including data source, method, and variables. Section 4 presents the empirical analysis. Section 5 gives the robustness tests, and the conclusions and discusses the key findings in the finally section.

2. Theoretical framework

2.1. VC investments and innovation

Technological innovation is a complicated systematic project, which is completed by enterprises, governments, scientific research institutions, and other departments (Popov and Roosenboom, 2012; Wadhwa et al., 2016). In the process of technological innovation, it is restricted by various factors (Coccia, 2009, 2017b; Wen et al., 2018), coupled with moral hazard and information asymmetry, which makes it more difficult for technological innovation to cross the “valley of death” of capital and management (Chen et al., 2011). VC can not only help enterprises alleviate capital difficulties, but also bring value-added services to entrepreneurial enterprises by utilizing its investment experience (Sonne, 2012).

VC has become an essential way for entrepreneurial enterprises to acquire innovative knowledge and technology resources (Belderbos et al., 2018; Wu and Xu, 2020). Entrepreneurial enterprises are generally small in scale, and lack tangible, assets credit ratings, and transparent financial information, thus leading to higher risks and uncertainties (Hall, 2002). These pose challenges for VC institutions, as it is difficult for them to evaluate the potential future development of these enterprises. As such, only a few VC institutions are willing to support them.

VC institutions apply their specific experience and sector-specific business knowledge to select potential enterprises to yield satisfactory investment returns and reduce the investment risks (Sahlman, 1990; Gompers and Lerner, 2001; Dushnitsky and Lenox, 2005; Belderbos et al., 2018). As professional equity investment institutions, VC institutions can facilitate the increase of enterprise value beyond providing financial resources (Kortum and Lerner, 2000; Dushnitsky and Lenox, 2005; Croce et al., 2013; Popov and Roosenboom, 2012; Lahr and Mina, 2016). In particular, VC has a long investment period and can increase investment according to different stages of the technological innovation life cycle of enterprises, which cannot be satisfied by traditional financing methods such as bank loans (Shahzad et al., 2019; Rehman et al., 2019; Wu and Xu, 2020). Also, VC institutions can conduct regular face-to-face information exchange and knowledge sharing with enterprises, increasing trust between them, and improving the business performance and innovation capabilities of entrepreneurial enterprises (Belderbos et al., 2018). Hence, it is considered as a better vehicle to provide financing for innovation by decision-makers.

Some studies have investigated whether VC affects the enterprise's performance (Gerasymenko et al., 2015; Lahr and Mina, 2015; Song et al., 2018), the probability of successful initial public offerings (IPO) (Bottazzi et al., 2008), enterprise's governance (Liao et al., 2014), and IPO discount (Otchere and Vong, 2016). However, few studies have discussed the influence of VC on the technological performance of the enterprise, and different conclusions have been reached. Some studies found that VC can improve the technological performance of the enterprise (Dushnitsky and Lenox, 2005; Hirukawa, 2008; Popov and Roosenboom, 2012; Bertoni and Tykvová, 2015; Brander et al., 2015; Alvarez and Dushnitsky, 2016; Sunny and Sun, 2018; Yang et al., 2018; Zhang et al., 2019). For example, Dushnitsky and Lenox (2005) and

[1] Wind Database: https://www.wind.com.cn.

Hirukawa (2008) presented that VC can promote technological innovation of enterprise, especially joint VC and private VC. Wen et al. (2018) showed that the impact of VC on technological innovation is nonlinear, and VC only has a positive effect on technological innovation when the investment scale exceeds the threshold level.

However, other studies suggested that VC has a negative effect or no effect on the enterprise's technological performance (Newbery, 2001; Lahr and Mina, 2015). Darby and Zucker (2005) pointed out that VC involvement has regional and industrial selectivity, and tends to invest enterprise with high labor quality and strong innovation ability. Still, it has no significant impact on technological innovation. Ni et al. (2014) found that VC can influence innovation, but its effect is limited. Lahr and Mina (2015) demonstrated that VC has no significant or negative impact on patent rights, and VC institutions should follow the patent signal to invest in commercially viable specialized technology enterprises.

2.2. Geographic distance and technological performance

Geographic distance refers to the spherical distance between VC institutions and enterprises, and it is an essential exogenous variable for the enterprise's technological performance (Cumming and Dai, 2010; Lutz et al., 2013; Guenther et al., 2018). VC institutions tend to exhibit geographic agglomeration (Coccia, 2004; Ivkovic and Weisbenner, 2005, 2008; Chen et al., 2010; Hoenen et al., 2014; Cheng et al., 2019). The principal-agent theory holds that a principal-agent relationship is formed between VC institutions and entrepreneurial enterprises, and information asymmetry and conflicts of interest between the two sides can lead to moral hazards and adverse selection. To reduce investment risks, VC institutions must effectively oversee, manage, guide, and communicate with entrepreneurial enterprises, and participate in their operation and management decisions (Sorenson and Stuart, 2008). The adverse selection before investment and the moral hazard after investment accompany the investment process. The difficulty of pre-evaluation and post-oversight leads VC institutions to have a strong preference for cooperating with enterprises in their geographic proximity (Gompers and Lerner, 2001).

Geographic distance affects the oversight efficiency of VC institutions on enterprises. As the geographic distance increases, the ability to oversee entrepreneurial enterprises decreases, increasing the investment risks of VC institutions. The VC institutions may choose to invest in entrepreneurial enterprises that are geographically close, while enterprises located at a long geographic distance have fewer opportunities to be invested. Moreover, with the increase of geographic distance, the transaction costs of VC institutions will increase, including screening cost, negotiation cost, oversight, and administration cost, etc. At the same time, the return on investment and willingness to invest may also be reduced, leading to insufficient research and development (R&D) funds for enterprises. This, in turn, may have a negative impact on the enterprise's technological performance (Cumming and Dai, 2010; Lutz et al., 2013; Guenther et al., 2018). VC institutions prefer geographic proximity, and reallocate cash flow and control rights as the spatial distance increase. This may further affect the enterprise's technological performance and regional economic development (Cumming and Dai, 2010; Lutz et al., 2013; Guenther et al., 2018).

2.3. Hypotheses

2.3.1. Heterogeneity of VC's equity backgrounds

There are many types of VC investors, each with different configurations of motivations and corresponding risk tolerance. Corporate VC (CVC), for example, refers to the use of corporate funds to invest in start-ups by taking minority stakes, which has become a particularly popular mechanism for established companies to access new markets and technologies from start-ups (Belderbos et al., 2018; Park et al., 2019). However, this study mainly focuses on the market-oriented VC that are purely financial in their pursuit of high returns. With respect to the equity backgrounds of VC institutions, VC can be characterized as governmental VC (GVC), private VC (PVC), and foreign VC (FVC) (Brander et al., 2010; Bertoni and Tykvová, 2015). GVC is oriented towards policy and public goods, and has the goal and task of promoting scientific and technological innovation, high-tech industrialization, and regional economic development (Fritsch and Schider, 2008). GVC institutions are affected by distance and have a “local investment preference”. Moreover, GVC institutions tend to have weak professional abilities, and most of the employees in their key positions are from government departments, which would lead to difficulty in adapting to marketization. Therefore, it is challenging to oversee and manage enterprises with long spatial distance effectively and to provide value-added services (Jääskeläinen and Maula, 2014).

PVC institutions are more affected by geographic distance (Bertoni and Tykvová, 2015). Compared with GVC institutions, PVC institutions have different funding sources, and they contribute to the innovation of entrepreneurial enterprises in a significantly different way. PVC and GVC institutions have different investment motivations, leading to significant differences in the output of technological innovation. FVC also differs from a GVC and PVC. FVC is completely marketized, highly specialized, and has greater international breadth (Dong et al., 2018). FVC institutions seek better investment projects in the global market, intending to pursue high short-term technology benefits and profits. Also, FVC institutions have more experience and can reduce the risk of space distance. Further, patents and other outputs from technological innovation take a long time, and these are not the primary goal of FVC institutions. Therefore, we hypothesize the following:

Hypothesis 1. The influence of geographic distance on the technological performance of enterprises differs from VC's equity backgrounds.

2.3.2. Heterogeneity of VC's strategies

VC's strategies mainly include joint VC (JVC) and independent VC (IVC). Both have different impacts on the technological performance of enterprises. JVC refers to two or more VC institutions that jointly invest in entrepreneurial enterprises and share operational risks and agency costs. In joint investment, the VC institutions have different experience and networks, and maximize their resource advantages (Brande et al.,2010; Chemmanur and Fulghieri, 2014; Alvarez and Dushnitsky, 2016; Siebert and Bernd, 2017). JVC can reduce the costs and risks arising from an increased geographic distance and can bring value-added services to enterprises (Lutz et al., 2013; Butler et al., 2013). This form of investment can also better identify and evaluate the risks of entrepreneurial enterprises, and better contribute to risk mitigation and resource sharing. More importantly, the joint investment by several VC institutions is a signal of the high quality of entrepreneurial enterprises.

IVC means that only one VC institution invests in an entrepreneurial enterprise. Most independent investors typically have experience and industry expertise, and tend to invest in cluster regions due to their preference for geographic proximity (Gompers and Lerner, 1999; Fritsch and Schilder, 2008). Because proximity in the distance can improve the investment performance of VC institutions in the supervision and management of entrepreneurial enterprises, and maximize the resources and relationship advantages of the VC institutions. Also, compared with JVC, IVC has relatively few resource relationships and experience, and has a low risk-bearing capacity. VC institutions tend to avoid risks and costs caused by the increase in geographic distance (Zou and Cheng, 2017).

In summary, as geographic distance increases, JVC can maximize the advantages and experience of VC institutions to reduce the problem of information asymmetry, reduce the agency cost and risk associated with entrepreneurial enterprises, and minimize the impact on enterprise innovation output. In contrast, the influence of IVC on technological performance is affected more by the increase of geographic distance. Therefore, we hypothesize the following:

Hypothesis 2. Different VC's strategies result in geographic distance having a different impact on the technological performance of enterprises.

2.3.3. The nonlinear effect of geographic distance on technological performance

In the most common form, VC institutions tend to invest in industries that have the potential to yield high returns. The risks in these industries are relatively high, but the returns, if realized, can also be considerable (Gompers and Lerner, 2001). The resource endowment of VC institutions has certain geographic limitations. Furthermore, even if most CVC investments aim to obtain an external knowledge-sourcing strategy, and they invest in promising businesses spread across locations, each with its expertise and skills. CVC investments are also affected by geographical distances (Belderbos et al., 2018). Therefore, the expansion of geographic distance increases the degree of information asymmetry and transaction costs. The advantages of VC institutions in evaluation, guidance, management, and resource integration begin to be challenged.

Some studies have shown that VC institutions often invest in proximity, because geographic proximity gives them an advantage in identifying, screening, and monitoring projects (Gompers and Lerner, 2001). At the same time, due to the advent of the network economy and the rapid development of information and communication technology, many VC institutions will also choose to invest at a long distance. For example, the high-speed railway network has expanded the geographic reach of VC institutions and reduced travel times in China. The expansion of accessibility means it is easier for VC institutions to communicate face-to-face with entrepreneurs in different places. Wallsten (2001) has investigated the aggregation effect of VC on innovation in different geographic distance circles, and divided the geographic distance into 12 ranges, including 0.1 miles, 0.5 miles, 1 mile, etc. Kolympiris et al. (2011) investigated the externalities of VC institutions on innovation, and divided the distances into three grades: 0–0.10 miles, 0.11–0.50 miles, and 0.51–1 mile. Sapienza et al. (2011) pointed out that the average distance between VC institution and enterprise is 1.5 h in the British, while the average distance in the United States is two hours. Qiao et al. (2018) divided the geographic distance into the following four levels: 0–360 km, 360–900 km, 900–1500 km, and 1500 km and above. Belderbos et al. (2018) found that CVC, as an additional form of VC, has an inverted U relationship between the geographic diversity of its portfolio and technological performance. In short, VC has a significant effect on the adjacent distance of enterprises' investment, but when the geographic distance exceeds a certain threshold, the effect of VC is not apparent. Therefore, we hypothesize the following:

Hypothesis 3. Geographic distance has a nonlinear effect on the technological performance of VC-backed enterprises.

3. Research design

3.1. Data

The enterprises included in this study were listed on the Chinese Growth Enterprise Market (GEM) from October 2009 to October 2012, and the data of the listed enterprises are from the period December 31, 2010, to December 31, 2017. The GEM listed enterprises from October 2009 to October 2012 are used as the samples for the following reasons. First, the characteristics of GEM listed enterprises are consistent with the strategic objectives of VC. Second, the GEM started in October 2009 in China, but IPOs were stopped from November 2012 to January 2014, and from July 2015 to November 2015. Finally, the patent application and authorization in China have lagged behind expectations. According to China's Patent Law, the patent administration department considers whether an application meets the requirements of the law after receiving the application for an invention patent, and the outcome is announced 18 months after the date of application. The patents for utility models and designs are announced after a preliminary examination. However, in practice, it usually takes 2–4 years from the application to the announcement. If the listed enterprises in recent years are selected, the span of the enterprise's data is too small to reflect the impact of VC on the technological performance of enterprises.

This study applies the following methods to determine whether VC supports the listed enterprises. First, we obtain a list of the top ten shareholders of the sample enterprises each year. Second, we compare the top ten shareholders with the VC directory in the Wind database[2] and "China venture capital development report (2010–2017)". If a shareholder is listed in the VC directory, the enterprise is considered as a VC-backed one. Finally, after identifying there are VC institutions among the top ten shareholders, we need to identify the equity backgrounds and the investment strategies of VC institutions. In this study, we use the Wind Database,[3] National Enterprise Credit Information Publicity System (NECIPS)[4], Tianyan Survey,[5] the official website of VC institutions, and other channels to identify the ownership attributes of VC institution.

All data are collected from Chinese authoritative databases to ensure the reliability and authenticity, such as the CSMAR database,[6] Wind Database, and China Research Data Service Platform (CNRDS) .[7] These data are checked with Juchao website[8] and the annual reports of the listed enterprises. During data processing, some enterprises are eliminated because too much data are missing, while missing data in some years are supplemented using the linear interpolation method. Also, the main variables are tailed off at the 1% level to exclude the influence of outliers. A total of 345 enterprises and 2542 enterprise-year samples are collected in this study.

The selected enterprises and VC institutions are statistically analyzed according to *the Guidelines on Industry Classification of Listed Enterprises* published by the China Securities Regulatory Commission (CSRC)[9] and regional distribution information. The results are shown in Appendix Tables A1 and A2.

3.2. Method

This study analyzes whether and how geographic distance influences the technological performance of VC-backed enterprises. Based on the above theoretical analysis, the test model is established as follows:

$$Y_{it} = \alpha_0 + \beta_1 distance_{it} + \beta_2 vc_{it} {*} distance_{it} + \beta_3 \ln size_{it} + \beta_4 \ln age_{it} + \beta_5 tag\_ratio_{it} + \beta_6 e\_ratio_{it} + \beta_7 indu_{it} + \beta_8 area_{it} + \varepsilon_{it} \quad (1)$$

where, Y is the dependent variable (technological performance); vc is an independent variable (VC); *distance* is also an independent variable (geographic distance); and ln*size*, ln*age, tag_ratio, e_ratio, indu* , and *area* are the following control variables: enterprise size, enterprise age, asset

[2] Wind database website: https://www.wind.com.cn.

[3] Wind database website: https://www.wind.com.cn.

[4] National Enterprise Credit Information Publicity System website: http://www.gsxt.gov.cn.

[5] Tianyan Survey website: https://www.tianyancha.com.

[6] CSMAR database website: http://www.gtafe.com.

[7] China Research Data Service Platform website: https://www.cnrds.com.

[8] Juchao website: http://www.cninfo.com.cn.

[9] The guideline, issued by the CSRC in 2001, includes 13 categories and was not revised until October 2012. Since the samples used in this study only include GEM enterprises listed between October 2009 to October 2012, this classification standard is adopted.

growth rate, equity ratio, industrial category, and enterprise location, respectively; the variable ε_{it} is a random error term; α_0, β_1, $\cdots$, β_8 represent the coefficients of each variable; i and t represent enterprise and year, respectively.

3.3. Variables

3.3.1. Dependent variable: technological performance

Based on the previous researches about the technological performance implications of entrepreneurial enterprises (Wadhwa et al., 2016; Belderbos et al., 2018), the technological performance is measured by the number of patent applications. Using the number of patent applications to measure the technological performance has many advantages. The patent administration department publicly grants a patent based on its novelty and utility, and the number of patents can be compared horizontally and vertically. Moreover, the patents capture three types of technological performance: invention, utility model, and design.

We count all three types of patents to create a total number of patent applications (Belderbos et al., 2018). In this study, the number of patent applications is logarithmized for reducing the bias. Since some enterprises do not have patent applications in some years, using the logarithm might produce outliers. Hence, the logarithm is calculated after adding 1 to all patent data. To ensure the reliability of the empirical results, a robustness test is conducted (described in Section 5) by replacing the number of patents with R&D investment. The R&D investment is measured using the ratio of R&D expenditures to the enterprise's operating income.

3.3.2. Independent variables: VC and geographic distance

The core explanatory variables in this study are VC (*vc*) and geographic distance (*distance*). VC is set as a dummy variable. If there are VC institutions in the top ten shareholders, then $vc = 1$, otherwise $vc = 0$. We also consider the heterogeneity of VC's equity backgrounds and VC's investment strategies. If the ownership of a VC institution is governmental (*vc_g*), then $vc\_g = 1$, otherwise $vc\_g = 0$. If the ownership of a VC institution is private, then $vc\_p = 1$, otherwise $vc\_p = 0$. If the ownership of a VC institution is foreign, then $vc\_f = 1$, otherwise $vc\_f = 0$. For investment strategy, if the strategy is a joint investment, then $vc\_joint = 1$, otherwise $vc\_joint = 0$. If the strategy is an independent investment, then $vc\_ind = 1$, otherwise $vc\_ind = 0$.

Some previous studies have shown that geographic distance can affect the choice of VC institutions (Fritsch and Schilder, 2008, 2012), which in turn affects the technological performance of enterprises. Geographic distance is measured as the distance between the registered location of the enterprise and the main VC institution (Tian, 2011). This study applies the method of Cumming and Dai (2013) to calculate the geographic distance, using the following steps: (1) Determine the main VC institution. If there is only one VC institution in an enterprise, it is the main VC. If an enterprise is invested by more than one VC institution, the VC institution with most shares is considered as the main VC. (2) Determine the registration place of the main VC institution and enterprise, and find the corresponding latitude and longitude. (3) The geographic distance between the main VC institution and the enterprise location is calculated according to the longitude and latitude. The calculation formula is constructed as follows:

$$
\begin{aligned}
distance_{ij} = \arccos\{ & \cos(Lat_i)\cos(Lon_i)\cos(Lat_j)\cos(Lon_j) \\
& + \cos(Lat_i)\sin(Lon_i)\cos(Lat_j)\sin(Lon_j) \\
& + \sin(Lat_i)\sin(Lat_j)\}\pi R/180
\end{aligned} \tag{2}
$$

where (Lat_i, Lon_i) represents the latitude and longitude of the registration location of enterprise; (Lat_j, Lon_j) represents the latitude and longitude of the registered location of VC institution; and R is the average radius of the earth.

3.3.3. Control variables

According to the studies of Liao et al. (2014), Song et al. (2018), Jebran et al. (2019), Zhang et al. (2020), etc., this study includes several control variables, which may influence the technological performance of enterprises. These are defined as follows:

(1) Enterprise age (ln*age*): It is defined by subtracting the establishment time from 2018.
(2) Enterprise size (ln*size*): It somewhat affects the technological performance of enterprises. We use the logarithm of total assets to measure enterprise size.
(3) Asset growth rate (*tag_rate*): It reflects the development ability and capital accumulation ability of enterprises. We use the ratio of the growth amount of the total assets at the end of the year to the total assets at the beginning of the year to measure this variable.
(4) Equity ratio (*e_ratio*): It is one of the indicators to measure the long-term solvency, and is used to evaluate whether the basic financial structure of an enterprise is stable. It is measured by the ratio of total liabilities to total owners'equity.
(5) Industry variable (*indu*): According to *the Guidelines on Industry Classification of Listed Enterprises* issued by CSRC in 2001, there are 13 categories of the businesses. It is a dummy variable and is set from 1 to 13.
(6) District variable (*area*): Regional difference is an essential factor affecting enterprise innovation, and the variable is measured according to the registered location of the enterprise. It is a dummy variable and is set from 1 to 3 (eastern = 1, central = 2, and western = 3).

Table 1 describes the details of the variables, and Table 2 provides descriptive statistics for all variables.

4. Empirical results

This study analyzes whether and how geographic distance affects the technological performance of VC-backed enterprises. First, we conduct an empirical analysis from the perspective of the heterogeneity of VC's equity backgrounds. Second, the heterogeneity of investment strategies, as either joint or independent, is empirically tested. Finally, we investigate the nonlinear impact of geographic distance on the technological performance of enterprises using the panel threshold regression model.

4.1. Heterogeneity of VC's equity backgrounds

Table 3 presents the regression results from the perspective of the heterogeneity of the VC's equity backgrounds. Among them, Column (1) represents the result when including geographic distance and the control variables; Columns (2), (3), and (4) are the results of adding the interaction terms between geographic distance and GVC, PVC, and FVC, respectively.

Column (1) in Table 3 shows that the coefficient of geographic distance is -0.3420, and it is statistically significant at the 10% level. They suggest that geographic distance has a significant negative impact on the technological performance of VC-backed enterprises. For every 1% increase in the geographic distance between the main VC institution and the enterprise, the number of patent applications decreased by 0.34%. The farther the distance is, the lower the impact of VC on the enterprise's technological innovation will be.

Column (2) in Table 3 also shows that geographic distance has a negative impact on the technological performance of enterprises, which is consistent with Column (1). The coefficient of the interaction term between geographic distance and GVC is significantly negative, and the effect of geographic distance on technological innovation of GVC-backed enterprises is -0.4071. These results indicate that the influence of GVC on the enterprise's technological performance is influenced by geographic distance.

Table 1
Description of variables.

Types	Variables	Symbols	Definitions
Dependent variables	Number of patent applications	ln*patent*	The logarithm of the total number of invention, utility model, and design patent applications.
	R&D Investment	*research*	The ratio of R&D expenditure to operating income.
Independent variables	VC	*vc*	If the enterprise is VC-backed, then $vc=1$, otherwise $vc=0$.
	Geographic distance	*distance*	The distance is calculated using the formula (2).
	GVC	*vc_g*	If VC institution is a GVC, then $vc\_g = 1$, otherwise $vc\_g = 0$
	PVC	*vc_p*	If VC institution is a PVC, then $vc\_p = 1$, otherwise $vc\_p = 0$.
	FVC	*vc_f*	If VC institution is a FVC, then $vc\_f = 1$, otherwise $vc\_f = 0$
	JVC	*vc_ joint*	If there are two or more VC institutions in the top ten shareholders of the enterprise, then $vc\_joint = 1$, otherwise $vc\_joint = 0$.
	IVC	*vc_ind*	If there is only one VC institution in the top ten shareholders of the enterprise, then $vc\_ind=1$, otherwise $vc\_ind = 0$.
Control variable	Enterprise size	ln*size*	The logarithm of total assets.
	Enterprise age	ln*age*	2018 minus the year that the enterprise was founded.
	Asset growth rate	*tag_ratio*	The ratio of the growth of the total assets at the end of the year to the total assets at the beginning of the year.
	Equity ratio	*e_ratio*	The ratio of total liabilities to total owner's equity.
	Industry	*indu*	The industry is a dummy variable and is set from 1 to 13.
	District	*area*	The district is a dummy variable: *eastern*=1, *central*=2, and *western*=3.

Table 2
The descriptive statistical analysis of all variables.

Variables	Number	Mean	S.D.	Minimum	Maximum
ln*patent*	2542	4.174	0.823	2.197	5.624
research	2542	6.857	5.847	0.157	35.220
vc	2542	0.330	0.470	0.000	1.000
ln*distance*	839	6.190	2.341	0.000	8.076
vc_g	2542	0.105	0.307	0.000	1.000
vc_p	2542	0.226	0.418	0.000	1.000
vc_f	2542	0.057	0.231	0.000	1.000
vc_ joint	2542	0.203	0.403	0.000	1.000
vc_ind	2542	0.127	0.333	0.000	1.000
ln*asset*	2542	21.155	0.772	19.568	23.252
ln*age*	2534	1.974	0.711	0.000	3.178
tag_rate	2534	0.459	0.764	−0.167	4.044
e_ratio	2542	0.449	0.431	0.030	2.235
indu	2542	4.352	2.407	1.000	13.000
area	2542	1.289	0.602	1.000	3.000

Table 3
Regression results of different equity backgrounds of VC institutions.

Variables	(1)	(2)	(3)	(4)
ln*distance*	−0.3420*	−0.3834**	−0.0217	−0.3539*
	(−1.91)	(−1.99)	(−1.07)	(−1.91)
ln*distance***vc_g*		−0.2260***		
		(−2.58)		
ln*distance***vc_p*			−0.2727**	
			(−2.38)	
ln*distance***vc_f*				−0.1201
				(−0.25)
ln*asset*	0.3043***	0.3035***	0.3096***	0.3052***
	(4.83)	(4.81)	(4.89)	(4.83)
tag_rate	−0.1249***	−0.1258***	−0.1250***	−0.1251***
	(−3.38)	(−3.40)	(−3.39)	(−3.38)
ln*age*	−0.1001	−0.1038	−0.1020	−0.1007
	(−1.45)	(−1.49)	(−1.46)	(−1.45)
e_ratio	−0.1661	−0.1669	−0.1701	−0.1664
	(−1.40)	(−1.40)	(−1.43)	(−1.40)
_cons	−4.7847**	−5.0484***	−2.6341	−4.8896**
	(−2.54)	(−2.60)	(−1.08)	(−2.52)
area	YES	YES	YES	YES
indu	YES	YES	YES	YES
year	YES	YES	YES	YES
Adj-R²	0.1487	0.1469	0.1396	0.1478
N	735	735	735	735

Note: *** $p \leq 0.01$; ** $p \leq 0.05$, and * $p \leq 0.10$; *t*-statistics are in parentheses.

Similarly, Column (3) shows that geographic distance is negatively correlated with the enterprise's technological performance. The coefficient of the interaction term between PVC and geographic distance is −0.2727, and the processing effect of PVC is −0.0886. These findings indicate that compared with GVC, the influence of PVC on the enterprise's technological performance is less affected by geographic distance. Column (4) shows that the coefficient of the interaction term between FVC and geographic distance is negative but not significant. These results provide the support that geographic distance does not significantly influence FVC-backed enterprises. The results of Columns (2), (3) and (4) indicate that the technological performance of GVC-backed enterprises is more influenced by geographic distance, compared with PVC- and FVC-backed enterprises. All of these results support hypothesis 1.

4.2. Heterogeneity of VC's strategies

Table 4 provides the regression results of different investment strategies of VC. Among them, Columns (1) and (2) in Table 4 are the test results after adding the interaction terms of geographic distance and JVC and IVC, respectively, based on Column (1) in Table 3. The results show that the coefficients of geographic distance are all

Table 4
Regression results of different investment strategies of VC institutions.

Variables	(1)	(2)
ln*distance*	−0.2609**	−0.4427**
	(−2.28)	(−2.05)
ln*distance***vc_ joint*	−0.2714***	
	(−3.83)	
ln*distance***vc_ind*		−0.3714*
		(−1.83)
ln*asset*	0.3069***	0.3079***
	(4.87)	(4.93)
tag_rate	−0.1237***	−0.1241***
	(−3.34)	(−3.65)
ln*age*	−0.0971	−0.1461
	(−1.40)	(−1.47)
e_ratio	−0.1703	−0.1603*
	(−1.43)	(−1.73)
_cons	−4.2686**	−5.5531***
	(−2.15)	(−2.64)
area	YES	YES
indu	YES	YES
year	YES	YES
Adj-R²	0.1537	0.1538
N	735	735

Note: *** $p \leq 0.01$; ** $p \leq 0.05$, and * $p \leq 0.10$; *t*-statistics are in parentheses.

significantly negative at a 10% level. This indicates that geographic distance has a significant negative impact on the technological performance of enterprises. These findings are consistent with previous conclusions in Section 4.1.

As Column (1) in Table 4 shows, the coefficient of the interaction term between JVC and geographic distance is −0.2714, which is negative at the 1% level of significance. When the VC institutions choose a joint investment, the processing effect of geographic distance on the technological performance of enterprises is −0.3160. This suggests that when VC institution adopts the joint investment strategy, each 1% increase in the geographic distance reduces the enterprise's technological performance by 0.32%. However, the coefficient of the interaction term between IVC and geographic distance is −0.3714 (Column (2)), which is significant at the 10% level. The processing effect of geographic distance on technological innovation is −0.4899. In other words, every 1% increase in the geographic distance leads to a 0.49% decrease in the technological performance of enterprises. These results support hypothesis 2 that geographic distance has a different impact on the technological performance of enterprises with distinct VC strategies.

Furthermore, the results show that the coefficient of IVC is more significant compared to that of JVC. This indicates that the IVC is more affected by geographic distance. The reason is that the joint investment strategy involves shared risks and agency costs, and the sharing of resources and information among VC institutions. In contrast, the independent investment strategy involves only one VC institution. As geographic distance increases, the cost of oversight and management increases, and even VC institutions cannot effectively oversee the R&D development of enterprises. Therefore, these results indicate that geographic distance has more influence on the technological performance of IVC-backed enterprises compared to JVC-backed enterprises.

4.3. The nonlinear effects of geographic distance

Although geographic distance has a significant impact on the enterprise's technological performance, it may have a nonlinear effect at different distance intervals. Some studies have found that geographic distance located in various ranges has different influences on the enterprises (Wallsten, 2001; Kolympiris et al., 2011; Wen et al., 2018). In this study, based on the research of Hansen (1999), we construct the panel threshold regression model to investigate the nonlinear impact of geographic distance on the technological performance of enterprises. The model is established as follows:

$$Y_{it} = \alpha_i + X_{it}\beta_1 \cdot I(q_{it} \le \gamma_1) + X_{it}\beta_2 \cdot I(\gamma_2 \ge q_{it} > \gamma_1) + X_{it}\beta_3 \cdot I(q_{it} > \gamma_2) + \omega_{it}\mathbf{W_{it}} + \varepsilon_{it} \tag{3}$$

where Y is the dependent variable (technological performance); X is the independent variable (VC or geographic distance); $\mathbf{W}$ is the following control variables: ln*size*, ln*age, tag_ratio, e_ratio, indu*, and *area;* γ_1 and γ_2 are the threshold values; q is the threshold variable; ε_{it} is a random error term; β_1, β_2, β_3, $\boldsymbol{\omega}$ represent the coefficient of each variable; i and t represent enterprise and year, respectively.

We first examine whether there is a threshold effect to determine the number of thresholds and models. Table 5 presents the test results

Table 5
Test results of the threshold effect.

Thresholds	F-value	P-value	Critical value 1%	5%	10%
Single	31.85**	0.0220	41.04	19.37	14.49
Double	28.25**	0.0142	33.77	17.59	12.96
Triple	3.50	0.6060	30.64	18.93	12.57

Note: (1) The two threshold values in double threshold are 470.73 and 1050.71, respectively; (2) The standard errors are calculated using Bootstrap with 1000 replications; (3) *** $p \le 0.01$; ** $p \le 0.05$, and * $p \le 0.10$.

Table 6
The estimation results of the panel threshold model.

Variables	(1)	(2)
vc	0.1231***	
	(3.10)	
ln*distance*		−0.1553***
		(−2.73)
ln*distance* (*distance* < γ_1)	−0.2977**	
	(−2.07)	
ln*distance* (γ_2 > *distance* ≥ γ_1)	−0.1334*	
	(−1.86)	
ln*distance* (*distance* ≥ γ_2)	−0.1013	
	(−1.06)	
vc (*distance* < γ_1)		0.8570***
		(2.90)
vc (γ_2 > *distance* ≥ γ_1)		0.4994**
		(1.99)
vc (*distance* ≥ γ_2)		−0.3095**
		(−2.12)
e_ratio	−0.0313	−0.0311
	(−0.47)	(−0.46)
tag_rate	−0.0674***	−0.0671***
	(−3.04)	(−3.03)
ln*size*	0.1632***	0.1629***
	(4.40)	(4.40)
ln*age*	0.1632***	0.1629***
	(4.40)	(4.40)
_cons	0.7619	0.7665
	(0.98)	(0.99)
area	YES	YES
indu	YES	YES
year	YES	YES
Adj-R^2	0.2176	0.2179
N	2542	2542

Note: (1) *** $p \le 0.01$; ** $p \le 0.05$, and * $p \le 0.10$; (2) *t*-statistics are in parentheses; (3) γ_1 and γ_2 are two thresholds, respectively.

of the threshold effect. The results show that the single threshold and double threshold are significant at the 5% level. In contrast, the triple threshold is not significant, indicating that geographic distance has a nonlinear effect on the technological performance of enterprises.

The regression results of the nonlinear effect are shown in Table 6. For the term of geographic distance in Column (1), their coefficients are significantly negative at the 10% level ($\boldsymbol{\beta}_1 = -0.2977$, $p < 0.05$;$\boldsymbol{\beta}_2 = -0.1334$, $p < 0.10$), when the geographic distance is lower than the first threshold (470.73 km) and the second threshold (1050.71 km), respectively. Nevertheless, the coefficient is negative but not significant ($\boldsymbol{\beta}_3 = -0.1013$, $p > 0.10$) when the geographic distance is higher than the second threshold value. More importantly, the coefficient of the first threshold is much higher than the coefficient of the second threshold.

The results in Column (2) show that there is an inverted U-shaped relationship between VC and technological performance at different geographic distance intervals. When the geographic distance is less than the threshold value (including the first threshold of 470.73 km and the second threshold of 1050.71 km), the coefficients of VC are significantly positive at the 5% level ($\boldsymbol{\beta}_1 = 0.8570$, $p < 0.01$; $\boldsymbol{\beta}_2 = 0.4994$, $p < 0.05$), indicating that VC has a significant positive impact on the technological innovation of enterprises when the geographic distance is close. However, when the geographic distance exceeds the second threshold value of 1050.71 km, its coefficient is significantly negative ($\boldsymbol{\beta}_3 = -0.1013$, $p < 0.05$), revealing that VC is not conducive to the improvement of enterprise's technological performance when the distance is far away.

5. Robustness tests

Due to some factors, such as self-selection bias, reverse causality, etc., there may be endogenous problems between geographic distance and technological performance. To reduce the possibility of estimation errors caused by endogenous problems, the process of tests is as follows:

Section 5.1 replaces the dependent variables for testing, Section 5.2 adopts alternative measures of independent variables, and the endogeneity tests are conducted in Section 5.3 using the two-stage strategy and the Propensity Score Matching (PSM) method.

5.1. Alternative measure of technological performance

To test the robustness of the results, this study uses the R&D investment as an alternative measure to evaluate the technological performance of enterprises, and Appendix Table A3 gives the test results. The results show that the coefficient of geographic distance is significantly negative at the 10% level for all models. The coefficients of interaction terms between geographic distance and GVC (Column (2)), and PVC (Column (3)) are significantly negative at the 5% level. The interaction coefficients of geographic distance and JVC (Column (5)) are also significantly negative. Although the interaction terms between geographic distance and FVC (Column (4)), and IVC (Column (6)) are not significant, the coefficients remain negative. In conclusion, after replacing the evaluation index for assessing the technological performance of enterprises, the empirical results remain robust and consistent with the previous findings.

5.2. Alternative measure of VC

VC, the VC's equity backgrounds, and VC's strategies are set as dummy variables. As such, it is difficult to find appropriate variables to replace them. This study applies the shareholding ratio of VC to test the robustness, including the shareholding ratio of GVC, PVC, FVC, JVC, and IVC. Appendix Table A4 displays the results of the robustness test. The data in the table shows that, except for Column (2), the geographic distance of all other models is negatively correlated with the technological performance of enterprises ($p < 0.10$). The interaction terms between geographic distance and GVC (Column (1)), and PVC (Column (2)) are significantly negative at a 5% level. The interaction term between FVC and geographic distance is not statistically significant (Column (3)). The interaction terms of geographic distance and JVC (Column (4)), and IVC (Column (5)) are all significantly negative. These results align with the research conclusions above, indicating that our research results are robust.

5.3. Endogeneity tests

Although some control variables are added to the regression in the study, it is still difficult to avoid endogenous problems caused by self-selection bias. Hence, we adopt the two-stage strategy and the Propensity Score Matching (PSM) method to conduct the endogeneity test.

(1) Two-stage strategy

We adopt the method of Surroca et al. (2010) to carry out the endogeneity test using the two-stage strategy, and this strategy has the advantage of tackling problems of multicollinearity and endogeneity. In the first stage, we construct instruments for geographic distance by regressing technological performance on independent variables and control variables, and then calculate the residual by subtracting the predicted effect from the dependent variable. The residuals have low correlations with the independent variables and control variables, thus avoiding multicollinearity.

In the second stage, we use the residuals as instrumental variables to test the existence of direct effects of geographic distance. Furthermore, we lag the residual by one period to control for potential reverse causality, and estimate the models using fixed effects (Surroca et al., 2010). More importantly, we use not only instrumental variables (lagged residuals) but also fixed effects for estimation. The process has addressed the issues of reverse causality and the possible correlation between independent variables and time-invariant unobservable heterogeneity (Surroca et al., 2010).

We have done this by lagging the residual by one period as the instrumental variable of geographic distance using the fixed-effect model. The results suggest that the residual is negative and significantly related to technological performance ($\beta = -0.2292$, $p < 0.05$) .[10] This indicates that there is no potential endogenous bias due to unobservable heterogeneity or inverse causality in our model estimates

(2) Propensity Score Matching method (PSM)

To avoid the “selective bias” caused by sample selection, this study uses the PSM method to evaluate the impact of geographic distance on the technological performance of the enterprise. First, we match the control and treatment groups with confounding variables that might have an effect on the enterprise's technological performance. These variables include VC's equity backgrounds, VC's strategies, and control variables (e.g., age, size, asset growth rate, equity ratio, industry, and area). The nearest neighbor matching method is used to match the control and treatment samples. All the characteristics of the identified paired control samples are similar to those of the treatment samples, except for the difference in geographic distance. Second, we compare the differences between the treatment and control samples in the technological performance of enterprises. The values of confounding variables in the treatment and control samples are very similar, so the possible influence of confounding variables on the technological performance of enterprises is controlled. Therefore, differences in the technological performance between two groups can be attributed to the geographic distance between VC institutions and enterprises.

Appendix Table A5 shows the comparison results of technological performance between treatment samples and control samples. As can be seen from the results, the number of patent applications and the R&D investment in the treatment samples are higher than those in the control samples. Although the two samples are similar in other characteristics, geographic distance still affects the technological performance of the enterprise, and geographic proximity is conducive to the improvement of technological performance. These results indicate that geographic distance between VC institutions and enterprises still has a significant negative impact on the technological performance of enterprise when the sample selection bias is controlled.

6. Discussions and conclusions

Entrepreneurship and innovation require the support of VC (Kortum and Lerner, 2000; Langeland, 2007). Although entrepreneurial enterprises, especially SMEs in the initial stage, have inherent technical advantages in some fields, they lack the benefits of continuous competition. This may hinder the technological innovation of enterprises, including better organizational structures, product-market recognition, economic capital, and social resources. VC institutions provide rich professional expertise, industry experience, financial capital, and social support. These offer value-added services to entrepreneurial enterprises, affecting their strategic choices and technological innovation capability (Wadhwa and Kotha, 2006; Van et al., 2011; Devigne et al., 2013; Hirukawa and Ueda, 2011).

The existing studies mainly focus on whether VC institutions prefer geographic proximity, and what factors affect the geographic proximity of VC institutions. However, few studies have examined the relationship between geographic distance and the technological performance of VC-backed enterprises. This study focuses on enterprises listed on the GEM in China, and investigate whether and how the geographic distance between VC institutions and enterprises influences the technological performance of enterprises. More importantly, this study empirically tests the different effects of geographic distance on technological performance under different equity backgrounds and strategies of VC institutions, and the nonlinear effect of geographic distance on technological performance.

This study makes several contributions to the existing literature. First, this study contributes to the literature by highlighting the impact

[10] The regression results are not reported duo to the limited space. If required, please contact authors for it.

of geographic distance on the technological performance of VC-backed enterprises. Our analysis confirms that geographic distance between VC institutions and enterprises has a nonlinear effect on the technological performance of the enterprises. When the geographic distance is less than the threshold value, the geographic distance is negatively correlated with technological innovation. In contrast, when the geographic distance exceeds the threshold value, it has no significant impact. Although different studies have drawn different threshold values from their conclusions, they all point out that there is a threshold effect between geographic distance and the enterprises' technological performance. And the influence becomes weak or insignificant after the geographic distance exceeds a specific threshold value (Wallsten, 2001; Kolympiris et al., 2011; Tykvová and Schertler, 2014).

There are several possible explanations for the above results. (1) As the geographic distance increases, it is difficult for VC institutions to oversee and manage the enterprises, and thus increasing the investment risk (Lutz et al., 2013). (2) VC institutions prefer to invest in entrepreneurial enterprises that are close to them (Cumming and Dai, 2010). (3) The transaction costs of distance increases, which reduces the investment returns of VC institutions. These factors may reduce the willingness of VC institutions to invest, and then affect the R&D investment of enterprises (Guenther et al., 2018).

Second, this study contributes to the literature more generally by demonstrating that geographic distance influenced the technological performance of enterprises differently when the VC institutions have different equity backgrounds (e.g., GVC, PVC, and FVC). More importantly, the results show that geographic distance has a more significant impact on the technological performance of GVC-backed enterprises compared to PVC- and FVC-backed ones, which is consistent with the studies of Jääskeläinen and Maula (2014) and Bertoni and Tykvová (2015).

These results may be due to the fact that VC institutions with different equity backgrounds experience significant differences in investment motivation, resource acquisition, and management and operation. Firstly, GVC institutions are more influenced by government policies, with a stronger invention orientation and a willingness to accept a long investment time (Fritsch and Schider, 2008). GVC institutions can also devote more resources to R&D activities. However, the farther the geographic distance is, the less the management will be accounted for, affecting the technological performance of enterprises. Then, compared with GVC institutions, PVC institutions have different funding sources and investment motives, and make significantly different contributions to the technological performance of enterprises (Bertoni and Tykvová, 2015). Hence, compared with GVC institutions, geographic distance has a more significant effect on PVC institutions concerning the technological performance of enterprises. Finally, FVC institutions have greater international breadth, rich investment experience, and reliable professional ability (Dong et al., 2018). These factors reduce the risk of geographic distance. The FVC institutions search good projects in the global market and pursue high short-tern technology advancements and returns. While technological performance is not their primary goal, because technological innovation, such as patents, take a long time.

More specifically, our findings suggest that the effect of JVC and IVC on the technological performance of enterprises is also influenced by geographic distance. Moreover, geographic distance has a more significant impact on IVC than on JVC. There are several reasons for the above results. First, as the geographic distance increases, the problem of information asymmetry between VC institutions and enterprises intensifies. It can be difficult for VC institutions to enter a co-located "network" of enterprises and obtain comprehensive information on the operation and management of enterprises. These can increase transaction costs and agency costs of VC institutions, reduce the input of R&D investments, and then affect the technological performance of enterprises (Jääskeläinen and Maula, 2014). Second, JVC can share risks and agency costs, realize network connections, and share resources and information among different VC institutions. However, for IVC, only one VC institution participates in the investment, and cannot share the risks and costs. As the distance increases, the oversight and management cost for VC institutions will increase, and it cannot effectively oversee the technological innovation of enterprises. Hence, geographic distance has significantly more influence on the technological performance of IVC-backed enterprises compared with JVC-backed ones.

Our study also provides significant insights into the VC practice in China. Past studies have mainly focused on the United States, Canada, Germany, and other developed countries. However, those conclusions do not apply for China's specific practices, because China's system differs from that of Europe and the United States (Wonglimpiyarat, 2016). Compared with VC institutions in Europe and North America, especially in the United States, the VC institutions in China started relatively late, and there is a significant gap in their investment experience and skills. Moreover, with the rapid development of science and technology, such as the construction of the high-speed rail network, VC institutions can spend the same time as before to communicate face-to-face with enterprises located farther away. This makes our results potentially useful for enterprise and government policymakers in China.

For enterprises, VC institutions provide not only more than just money but also advice and networks. Enterprises should be aware that the impact of geographic distance on the technological performance of enterprises differs with the heterogeneity of VC institutions. Decision-makers should prioritize GVC institutions and PVC institutions that are geographically close and adopt a joint investment strategy. For the government, policies should be issued according to the characteristics of the VC's equity backgrounds and VC's strategies. The government should guide GVC institutions and PVC institutions to invest in local enterprises, attract leading FVC institutions from around the world, and encourage them to invest jointly with two or more VC institutions.

A potential limitation of our research is that we mainly focus on the impact of geographic distance between VC institutions and enterprises on technological performance. Our goal is to understand better the effect of geographic distance on enterprise's technological performance from different VC's characteristics. Hence, we do not consider the other aspects, such as the high-speed rail network, e-communication, VC platforms, etc. Another limitation is that data constraints do not allow us to investigate all the VC-backed enterprises, especially for SMEs that are not listed on the stock market. Future work should further explore the influence of geographic distance on the technological performance of enterprises in different industries and countries. Finally, our study could not take into account whether the impact of CVC as a particular type of VC on enterprise's technological performance is affected by geographical distance. In fact, CVC investments are also affected by geographical distance. With the increase of geographic distance, the ability to take optimal advantage of knowledge endowments in the portfolio may decrease (Belderbos et al., 2018). Consequently, we should analyze from the geographic diversity of the CVC investment portfolio and explore its impact on the enterprise's technological performance in the future.

CRediT authorship contribution statement

Xiaoli TIAN: Conceptualization, Writing - original draft, Software. **Gang KOU:** Methodology, Writing - review & editing. **Weike ZHANG:** Data curation, Software, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare no conflict of interest.

Acknowledgments

The authors would like to acknowledge the financial support from the Fundamental Research Funds for the Central Universities of Sichuan University (2020Ziyan-Gongguan02), and the National Natural Science Foundation of China (71910107002).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.techfore.2020.120155.

Appendix

Table A1– A5

Table A1
The industry distribution of sample enterprises.

Industry category	Code	Number	Proportion (%)
Agriculture, forestry, animal husbandry and fishery	A	32	1.26
Mining	B	22	0.87
Manufacturing	C	1752	68.92
Production and supply of electric power, gas and water	D	12	0.47
Construction	E	23	0.90
Transportation and storage	F	0	0
Information transmission, software and information technology services	G	479	18.84
Wholesale and retail trade	H	37	1.46
Finance and insurance	I	6	0.24
Real estate	J	0	0
Social services	K	66	2.60
Communication and cultural industry	L	27	1.06
Comprehensive	M	86	3.38

Note: According to guidelines on industry classification of listed enterprises issued by CSRC in 2001, if the proportion of the operating income of a certain type of enterprise's business is greater than or equal to 50%, it will be classified into the corresponding category of the business. When the proportion of any business of the enterprise is less than 50%, if the proportion of operating revenue of a business is 30% higher than that of other businesses, the enterprise will be classified into the corresponding industry category of such business. Otherwise, it is classified as a comprehensive class. For example, scientific research and technical services enterprises and education enterprises are classified into comprehensive category.

Table A2
The regional distribution of sample enterprises and VC institutions.

Region		Sample enterprise		VC institution	
Code	Name	Number	Proportion (%)	Number	Proportion (%)
District 1	Eastern	2006	78.91	570	80.06
District 2	Central	337	13.26	64	8.99
District 3	Western	199	7.83	78	10.95

Note: According to the regional development plan in China, the eastern region includes 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes eight provinces: Heilongjiang, Jilin, Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes 12 provinces: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Tibet.

Table A3
Robustness test (replace the dependent variable with R&D investment).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ln*distance*	-0.6810^{***}	-0.3127^{**}	-0.4169^{**}	-0.3787^{***}	-0.4478^{*}	-0.2437^{**}
	(-2.67)	(-2.30)	(-2.34)	(-3.73)	(-1.90)	(-2.21)
ln*distance* **vc_g*		-0.3664^{**}				
		(-2.39)				
ln*distance* **vc_p*			-0.3074^{**}			
			(-2.44)			
ln*distance* **vc_f*				-0.3807		
				(-1.34)		
ln*distance* **vc_ joint*					-0.3494^{***}	
					(-2.88)	
ln*distance* **vc_ind*						-0.4475
						(-0.88)
control variable	Yes	Yes	Yes	Yes	Yes	Yes
area	Yes	Yes	Yes	Yes	Yes	Yes
indu	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	0.1465	0.1540	0.1533	0.1471	0.1455	0.1476
N	735	735	735	735	735	735

Note: *** $p \le 0.01$; ** $p \le 0.05$, and * $p \le 0.10$; t-statistics are in parentheses.

Table A4
Robustness test (replace the index of VC with shareholding ratio of VC).

Variables	(1)	(2)	(3)	(4)	(5)
ln*distance*	−0.3505***	−0.2340	−0.3593**	−0.3383*	−0.3051*
	(−2.91)	(−1.22)	(−1.96)	(−1.84)	(−1.69)
ln*distance*	−0.0485**				
**vc_g*	(−2.22)				
ln*distance*		−0.0467**			
**vc_p*		(−2.39)			
ln*distance*			−0.0157		
**vc_f*			(−0.47)		
ln*distance*				−0.0231**	
**vc_ joint*				(−2.10)	
ln*distance*					−0.0118*
**vc_ind*					(−1.81)
control variable	Yes	Yes	Yes	Yes	Yes
area	Yes	Yes	Yes	Yes	Yes
indu	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Adj-R^2	0.1499	0.1432	0.1470	0.1480	0.1501
N	735	735	735	735	735

Note: *** $p \le 0.01$; ** $p \le 0.05$; * $p \le 0.10$; *t*-statistics are in parentheses.

Table A5
Comparison between treatment sample and control sample.

Variables	Sample	Treated	Control	Difference	t-value
ln*patent*	Unmatched	4.1872	4.1920	−0.0048	−0.05
	Matched	4.1904	3.9456	0.2448***	2.75
research	Unmatched	9.3851	8.0346	1.3505	1.07
	Matched	9.3372	7.0749	2.2623***	3.72

Note:*** is significant at 1% level.

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