Essays on Venture Capital Investment

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Abstract

The thesis focuses on Venture Capital (VC) investments. This thesis contributes to the VC literature and advances the understanding of venture capital by shedding light on the interplay between VC local experience and geographic distance on investment decisions and partnership performance, impact of VC diversification strategies, and the role of VC monitoring in enhancing director accountability.

In the first chapter, we investigate the interplay between VC local experience, geographic distance, and their influence on investment decisions and subsequent partnership performance. Leveraging hand-collected data on first-time VC investments in biotechnology firms worldwide, observed over the period from 2010 to 2019, we examine how VC local investment experience moderates the negative relationship between geographic distance and the likelihood of engaging in later-stage investments. Surprisingly, while VC local experience does moderate investment decisions, it does not seem to foster follow-on funding and successful exits in partnerships involving geographically distant VCs and portfolio firms. The results are robust to a series of sensitivity and endogeneity tests, shedding light on the nuanced dynamics of VC experience and geographic distance in the VC investment landscape.

After examining how VC investment decisions are influenced by geographic distance, the second chapter delves into the impact of VC diversification strategies on the operational and financial performance of portfolio firms. Using a hand-collected panel data set comprising 401 VC-funded UK companies observed over the period from 2009 to 2019, we examine the influence of VC expertise gained from prior active investments compared to the coordination costs associated with concurrent active investments in firms with diverse business activities. The results highlight that expertise obtained from VCs' diverse prior experiences positively correlates with portfolio firms' performance. Conversely, coordination costs from VCs' concurrent diversification show a negative association with portfolio firms' performance.

In the third chapter, we focus on the impact of VC monitoring on director accountability within portfolio firms. Through an empirical analysis of a sample of UK companies observed over the 2009-2019 period, we explore whether director turnover is more sensitive to firm performance in firms backed by VC compared to those without VC support. The findings consistently demonstrate higher director turnover in VC portfolio firms experiencing lower performance and growth. Our results remain robust when considering alternative performance measures and estimation methods, suggesting that VCs contribute to enhancing director accountability for portfolio firm performance.

Key words: venture capital, VC diversification, portfolio firms, VC monitoring, director turnover, geographic distance, investment stage decision, VC local experience.

Introduction

Venture Capital (VC) has emerged as a vital force in driving innovation, fostering entrepreneurship, and fuelling economic growth (Galloway et al., 2017). As an essential component of equity finance, VC plays a crucial role in funding high-potential start-ups and enabling their transformation into successful scale-ups. However, the performance of VC firms and VC portfolio firms, and the nature of VC investment are subjects of intense scholarly inquiry. This thesis aims to contribute significantly to the VC literature by providing comprehensive insights into these critical areas such as VC experience, VC diversification strategy, and VC monitoring.

The nature of VC investment is distinctive and plays a pivotal role in financing innovative and high-growth potential start-ups and early-stage companies. Unlike traditional sources of funding, VC investors take on higher risks by providing capital to businesses with unproven track records, novel ideas, and significant growth potential. In addition, VCs can add value beyond just providing financial capital. For example, VCs often have a broad network of industry contacts that can be leveraged to help the company grow. They may introduce the company to potential customers, suppliers, or strategic partners.

Equity financing provides companies with an opportunity to secure funds without incurring debt, which can be particularly advantageous for startups and early-stage ventures that may not have sufficient assets or cash flow to support traditional borrowing (Drover et al., 2017). VC investors usually acquire an equity stake in the companies they invest in, meaning they become partial owners. This equity ownership aligns the interests of the investors with the entrepreneurs, as both parties share in the potential gains and losses of the venture.

The demand and supply characteristics of equity finance are influenced by various factors, including economic conditions, interest rates, investor confidence, industry trends, and the overall investment climate. In robust economic environments with high investor confidence, the demand for equity finance may increase as entrepreneurs seek capital to fund ambitious ventures. On the supply side, factors such as the availability of venture capital funds, investment appetite, and risk tolerance of investors also impact the accessibility of equity financing options.

There are various types of investors in equity finance including VC funds, business angels, government funds, and crowd funding and so on. Each type of investor may have distinct investment criteria, risk appetite, and levels of involvement in the companies they fund, offering diverse options for entrepreneurs seeking equity financing. VC investment is heavily biased towards companies that offer innovative products, services, or technologies. Investors seek out ventures with disruptive ideas that have the potential to transform industries and create new markets.

VC investors typically manage diversified portfolios to spread risk. They invest in multiple companies across different industries and stages of development. Diversification helps mitigate the impact of potential failures and allows investors to capture returns from successful ventures. However, When a VC firm invests in multiple companies within the same or related industries, synergies can arise. Portfolio companies may collaborate, share knowledge, or develop complementary products or services, creating a mutually beneficial environment. Synergies between investees can lead to enhanced innovation, cost savings, and market expansion opportunities.

Challenges exist in defining sectors in the VC sphere as many industries within the VC sphere, such as technology and biotechnology, undergo rapid and disruptive changes. New sub-sectors and niches emerge, while others become obsolete. Defining precise sectors can be challenging due to the fluidity and constant evolution of these industries.

There are four stages in the VC investment cycle: seed stage (seek seed funding or early-stage investment to develop their concepts and establish a viable business model), early stage (require additional funding to scale their operations), expansion stage (seek larger rounds of financing to expand into new markets, develop new products, and further increase their market share), and later stage (seek additional capital for strategic acquisitions, global expansion, or preparation for a potential exit).

Investing in early-stage start-ups is inherently risky, and failure rates can be relatively high. Many start-ups do not survive beyond the initial stages due to factors such as market competition, lack of product-market fit, inadequate funding, or poor execution. Studies have shown that a significant percentage of start-ups fail within the first few years of operation (Shahzad et al., 2021). However, successful investments that achieve high growth and profitability can deliver substantial returns, compensating for the failures and generating overall positive returns for VC investors.

VC firms often prefer to keep portfolio firms geographically close to their headquarters. Being physically close to portfolio firms allows VC investors to have more direct and frequent interactions with company founders and management. This proximity facilitates active involvement, mentoring, and support in crucial decision-making processes.

Intangible assets, such as patents, trademarks, copyrights, and trade secrets, are crucial for many start-ups and early-stage companies. These assets provide a competitive advantage and can significantly contribute to the company's valuation and attractiveness to investors. Having patents and trademarks can act as signalling mechanisms for investors, indicating that the company possesses unique intellectual property and a defensible market position. Such protections can bolster investor confidence in the start-up's potential for success, making it more attractive for VC funding.

Exit strategies are crucial for VC investors since they enable VCs to monetise their equity stake and achieve financial gains. Venture capitalists often realise their return on investment and exit via initial public offerings (IPO), merger and acquisition (M&A), secondary sale, and liquidation. Each exit route has its own set of risks and benefits. For example, an IPO may provide a higher return on investment but could be more time-consuming and complex than an acquisition.

This thesis has implications for policy makers, helping them recognize the critical role of VC in promoting innovation and performance, fostering entrepreneurship, and driving economic growth. They should implement policy interventions to support and enhance the VC ecosystem. Policy interventions aim to create a favourable environment for entrepreneurs, removing barriers and providing incentives for them to take risks and pursue their entrepreneurial aspirations. In addition, VC financing can be concentrated in certain regions or urban centres, leaving other areas underserved. Policymakers may implement measures to promote regional development by encouraging VC investments in economically disadvantaged or remote regions.

Chapter 1: The moderating effects of local investment experience and patenting activities on distant VC investment: Evidence from the biotechnology industry

Abstract

The chapter investigates whether venture capital (VC) local experience and geographic distance interact to affect investment-stage decisions and subsequent partnership performance. The analysis uses hand-collected data for first-time VC investments in biotechnology firms across the world observed over the 2010-2019 period. We find that VC local investment experience moderates the negative relationship between geographic distance and the likelihood of engaging in later-stage investments. However, VC local experience does not seem to foster follow-on funding and successful exits in partnerships involving geographically distant VCs and portfolio firms. The results are robust to a series of sensitivity and endogeneity tests.

Key words: geographic distance; local experience; investment-stage decisions; follow-on funding; successful exits.

1. Introduction

Even with the latest technological advancements, geographic distance is still a potential factor that is often incorporated in VC pre-screening activities and post-investment monitoring. One of the downsides of reliance on telephonic meetings is that the richness of conversations is reduced. On the contrary, real face-to-face time with people enhances reciprocal trust, thereby improving the quality of decisions made.

Geography matters to VCs when making investment decisions. VCs need to spend considerable time conducting due diligence. Geographic distance can directly impact the process of due diligence on entrepreneurial firms and thus affect their investment strategies and types. VCs play an actively monitoring role after investment by frequently visiting portfolio firms, having conversations with executives, and participating in board meetings. A similar cultural concept promotes communication and mutual understanding. Also, monitoring costs can be reduced if portfolio firms are located nearby. Therefore, geographic distance may be determinants to the effectiveness of monitoring. Recently, the internationalisation of VC investors has become more popular, but it is also accompanied by main concerns such as information asymmetry and moral hazard (Dai et al., 2012). There is a need to investigate what factors help distant VCs improve the uncertainties and risk preferences.

Although geographic distance creates barriers for VC investors to monitor their portfolio firms, the phenomenon of early-stage investments by distant VCs still exists and is becoming popular because the development of products requires the recombination of external knowledge which is not available locally, especially in the context of the biotechnology industry. Moreover, empirical papers have found that geographic distance has a negative influence on VC investment outcomes (Tian, 2011) and foreign VCs have stronger willingness to form syndications than domestic ones (Wang, 2017). However, prior investment experience in the same city as the current venture (i.e. local investment experience) will benefit VCs due to the familiarity with the local business environment and establishment of local networks. Therefore, one of the purposes of this project is to investigate whether local investment experience can assist VCs to overcome geographic distance.

This paper will focus on the biotechnology industry for several reasons. First, biotechnology companies have to experience a long cycle of product development with substantial risks and uncertainties. The effect of distance is more likely to be incorporated in the VC decision-making process. Second, since biotechnology firms require a higher level of know-how that may not be available locally, distant VC investments may frequently occur in this industry. Third, biotechnological companies encounter greater risks, and experience is crucial for not only the monitoring of VCs but also the performance of biotechnology firms, which provides an excellent background to examine the importance of VC local investment experience. If local investment experience is helpful for VCs to overcome geographic distance, the moderating effects can be detected in the biotechnology industry. Finally, the biotechnology industry enables us to examine the signalling effect of patent activities on VC investment decisions and outcomes.

This project will contribute to the extant VC literature. First, we extend the research by Dai et al. (2012) who find that international VCs are more likely to invest in information-transparent ventures than domestic VCs. However, they do not empirically examine whether geographic distance impacts on VC early-stage investment decisions. We will conduct a finer-grained analysis by investigating the unexplored impact of geographic distance on decision-making of investment stages, and this is the starting point of our research. Second, the question of what makes VCs still willing to make distant investments despite the information-related challenges remains unanswered. We contribute to the literature of VC human capital by highlighting the importance of VC local investment experience on investment decisions and outcomes in the context of distant investments. Although prior works find a negative relationship between geographic distance and investment outcomes, we argue that familiarity with local environments alleviates the concerns about investment uncertainty and assists VCs to build self-confidence so that they are more likely to invest in early-stage ventures.

This paper is structured as follows: the next section is hypothesis development. Section 3 is model specifications. Section 4 illustrates samples and variables. Section 5 and section 6 show summary statistics and empirical results respectively. Section 7 conducts robustness checks. Section 8 is additional analysis. Finally, section 9 provides the discussion and conclusion.

2. Hypotheses development

The concentration of VC investees in specific regions, such as London, the Southeast (SE), and the East of England, is a prominent characteristic of the UK's start-up ecosystem. These areas have become hotspots for entrepreneurial activity and innovation due to a combination of factors, including access to talent, research institutions, supportive infrastructure, and established networks. Start-ups in these regions often form clusters, where a concentration of companies within a specific industry or sector emerges. Clusters promote knowledge sharing, facilitate access to suppliers and customers, and stimulate innovation through the exchange of ideas. In the UK, VC investees often form syndicates consisting of various investor types. Syndicates bring together multiple investors, including angel investors, venture capital firms, corporate venture arms, and government entities. Foreign VC firms, particularly from the USA and China, are prominent players in the UK's VC landscape. These foreign funds often target later-stage investments, specifically scale-up companies that have demonstrated significant growth potential. Many foreign VC firms establish local offices in key cities like London to better understand the local ecosystem, build relationships, and provide hands-on support to their portfolio companies.

Researchers have shown greater interests in examining what factors impact VC investment decisions and patterns (Chircop et al., 2020; Paik and Woo, 2014; Chaplinsky and Gupta-Mukherjee, 2016). For example, Paik and Woo (2014) demonstrate how VC investment decisions can be affected by macroeconomic factors. They find that the likelihood of VC early-stage investment rises when there is increasing capital flowing into the market. Early-stage innovative start-up companies are more (less) likely to be financed by VCs during economic downturns related to the financial sector (real sector) compared to later-stage counterparts. However, the effect of other factors, such as information asymmetries arising from geographic distance, on the VC investment decision-making process remains unstudied.

Early-stage investments encounter greater uncertainty and risks. The lack of an extensive track record of performance for companies at an early stage causes difficulties in conducting due diligence (Chaplinsky and Gupta-Mukherjee, 2016). Monitoring intensity is closely related to early-stage ventures to prevent investment failure. However, information asymmetry is a concern when investors are distant from their investee firms. Being far away from portfolio firms symbolises an obstacle negatively affecting investors' monitoring function (Berns et al., 2021). Accordingly, firm behaviour and functioning are significantly influenced by geography.

Distant investment increases the possibility of "window dressing" due to information asymmetries between venture capitalists and portfolio firms. Since "window dressing" provides inaccurate information to VC investors, the benefit of stage financing is reduced. In order to mitigate the risks, distant VCs can invest in a later-stage round because of more clearly available information about firms' governance and internal control.

Physical proximity allows VCs to conduct more thorough due diligence because of convenience in collecting information. However, geographic distance results in constraints to gather soft information (e.g. motivation, goals, and expectations) (Chakrabarti and Mitchell, 2016). Consequently, VCs would be resistant to early-stage investment implementation.

To mitigate the information asymmetries and monitoring costs, foreign VC firms tend to choose more transparent firms than domestic VC counterparts. Namely, they are more likely to invest in companies at a later stage or in later financing rounds (Dai et al., 2012). Although domestic VCs are not subject to cultural disparity and institutional difference, geographic distance can be still a hindrance to monitoring efficiency.

Geographic proximity promotes interactions between companies, offers more opportunities for investors to exploit local knowledge, and facilitates relationship formation. Distant VCs are disadvantageous as it is hard to make opaque information more transparent. For instance, they face higher costs to reduce information friction due to less frequent face-to-face interactions with the founding team of entrepreneurial firms and less local experience.

H1: Geographic distance increases the likelihood that VCs opt for later-stage investments rather than early-stage investments.

Local investment experience helps VCs increase familiarity with local environments, govern business relationships, and mitigate information asymmetries. Local knowledge facilitates VCs to develop strategies to overcome the obstacles owing to geographic distance. Prior investments in the local market expose VCs to local business partners resulting in the establishment of networks. Further, local networks enable VC investors to more easily find promising ventures, gather more transparent information about the specific venture, and assess the target venture's quality and potential.

In some countries, like the United States of America, different states may have different laws. In this case, prior local investments familiarise VCs with the local market mitigating the concerns about the potential violation of local business laws. Due to historical reasons, different legal systems are derived from different geographical areas in the United Kingdom. Distinct legal jurisdictions may affect investment behaviour and highlight the importance of local investment know-how.

Despite the existence of issues arising from geographic distance, local investment experience can be helpful for foreign VC investors to overcome the challenges. Li et al. (2014) assert that with country-specific experience, foreign VCs are able to better understand the environments of the host country's institutions and culture. Local market investment expertise is expected to have stronger effects on decision-making than country-wide experience because of a deeper understanding of local environments. Compared to domestic VCs, foreign VCs encounter greater information asymmetries which create opportunities for adverse selection. In this case, the ability to access local networks assists VCs to better screen risky ventures, avoid moral hazards, and they are more likely to invest in informationally opaque entrepreneurial firms. Deeper understanding about the local culture through prior local investments also alleviates post-investment agency conflicts.

The level of information availability affects the completion of early-stage investments. The ability to access fine-grained information about investee companies is crucial for VC investors to make decisions about whether to invest at an early stage or pending their investment until a later stage when information becomes more transparent. While previous studies suggest that geographic distance between VCs and portfolio firms is associated with monitoring costs, we argue that local investment experience can mitigate the negative effects of geographic distance on investment concerns.

H2: Prior local investment experience attenuates the preference of distant VCs for later-stage investments.

In addition to the advantages of familiarity obtained from previous investment experience in the host country, VCs can also establish a good relationship with local partners. Prior collaboration ties benefit VCs as they allow them to combine resources and knowledge from various channels. Further, local investment experience is helpful in mitigating transaction and monitoring costs and gaining legitimacy. Accordingly, VCs equipped with local investment experience can maintain or achieve better partnership with portfolio firms.

Familiarity with the local market and the ability to access local networks and knowledge determine the effectiveness of VC value-added services such as providing advice to portfolio firms and resolving incentive conflicts (Buchner et al., 2018). Since there is a high level of competition among VCs due to a limited number of attractive investment opportunities (Paik and Woo, 2014), networking supplies VCs with advantages such as quicker access to these opportunities and a higher rate of return in future exits. Local embeddedness allows VCs to constantly and efficiently discover new information and update their evaluations for portfolio firms, which in turn better analyses ventures' needs and provides corresponding resources and suggestions.

VCs which are located in the same location as their portfolio firms have a competitive advantage compared to other VCs from somewhere else. Local VCs are less likely to suffer from adverse selection and moral hazard problems and possess greater bargaining power. Cumming and Dai (2010) find that "local bias" becomes stronger for lead VC and that the bias can be alleviated by broader networks. While the absence of geographic proximity leads to "local bias", making it harder to monitor portfolio firms and maintain a good relationship with backed firms' management, local exposure and embeddedness are beneficial in terms of reducing such bias so that some potential conflicts can be avoided. Furthermore, direct experience associated with the local market improves the capability of information gathering and assessment leading to better target selection.

In terms of cross-border deals, "foreignness of liabilities" arising from geographic distance, institutional difference, and cultural disparity result in higher transaction costs, information asymmetries, and agency problems (Buchner et al., 2018). When making investments in an unfamiliar environment, venture capitalists will lack the awareness of local social and cultural practices. However, it is expected that having local investment experience can alleviate these problems and thereby help international VCs better cooperate and coordinate with investee firms.

H3: Local investment experience enhances the likelihood that distant VCs achieve successful VC-startup partnerships.

VC investment decisions are based on the information that they are able to collect. Patent activity of portfolio firms has a strong signalling effect which shows firms' innovation ability. Hoenen et al. (2014) find that portfolio firms at the first financing round can raise substantial findings with the increase in the number of submitted patent applications, while patent applications and granted patents have no significant impacts on the level of received investment amount. Their results highlight the importance of portfolio firms' patent activity before the first financing round. Since young ventures lack the performance track record, patent activity is one of the main sources for venture capitalists to evaluate the potential of ventures' future development. VCs will be willing to invest in early-stage ventures when they perceive the likelihood of greater success. Patents, entrepreneurial companies have secured, are able to send a positive signal to VC investors showing their persistence in developing innovation ability.

Patent activity is a premise for the development and survival of biotechnological firms. Compared to granted patent and patent citation, patent applications may convey stronger signalling values by showing that portfolio firms do not sit idle and are proactively pursuing sustainable growth (Hoenen et al., 2014).

H4 (a): The portfolio firm's patenting activity influences the VC's likelihood to invest in later-stage investments.

H4 (b): The portfolio firm's patenting activity influences the VC's likelihood to achieve successful VC-startup partnerships.

3. Model specifications

As our dependent variables are binary variables, the logit model is preferable to use for this non-linear estimation. Maximum likelihood estimation (MLE) is applied to estimate the model.

$$P(y=1|x) = F(x, \beta) = \frac{\exp(x'\beta)}{1+\exp(x'\beta)}$$

To examine the first hypothesis, we implement the following model. A positive a_1 indicates that distant VCs are more likely to invest in later-stage portfolio firms and thus supports hypothesis 1. The μ_i is an error term across all regression models.

$$\text{Later stage} = a_0 + a_1\text{Distance} + a_2\text{Local Exp} + a_3\text{Co-Investors} + a_4\text{VC Equity Amount} + a_5\text{CVC} + a_6\text{GVC} + a_7\text{VC Age} + a_8\text{VC Past Success} + \text{Year Dummy} + \text{Country Dummy} + \mu_i \quad (1)$$

Then we add the interaction term between geographic distance and VC local investment experience to verify hypothesis 2. If the coefficient b_3 is significantly negative, the result would suggest a negative moderating effect of VC local investment experience on the relationship between geographic distance and investment stage.

$$\text{Later stage} = b_0 + b_1\text{Distance} + b_2\text{Local Exp} + b_3\text{Local Exp*Distance} + b_4\text{Co-Investors} + b_5\text{VC Equity Amount} + b_6\text{CVC} + b_7\text{GVC} + b_8\text{VC Age} + b_9\text{VC Past Success} + \text{Year Dummy} + \text{Country Dummy} + \mu_i \quad (2)$$

Since we use different dependent variables to test hypothesis 3, different control variables may be adopted in different models. For example, a round number is appropriate to examine the likelihood of VC successful exits but is not proper to be used in model 3 because of forward-looking bias. Venture age and stage dummy are controlled in models 3-4. The positive coefficients of c_3 and d_3 will support hypothesis 3.

$$\text{Follow-on Funding} = c_0 + c_1\text{Distance} + c_2\text{Local Exp} + c_3\text{Local Exp*Distance} + c_4\text{Co-Investors} + c_5\text{VC Equity Amount} + c_6\text{CVC} + c_7\text{GVC} + c_8\text{VC Age} + c_9\text{VC Past Success} + c_{10}\text{Venture Age} + \text{Year Dummy} + \text{Country Dummy} + \text{Stage Dummy} + \mu_i \quad (3)$$

$$\text{Successful Exits} = d_0 + d_1\text{Distance} + d_2\text{Local Exp} + d_3\text{Local Exp*Distance} + d_4\text{Co-Investors} + d_5\text{VC Equity Amount} + d_6\text{CVC} + d_7\text{GVC} + d_8\text{VC Age} + d_9\text{VC Past Success} + d_{10}\text{Round Number} + d_{11}\text{Venture Age} + \text{Year Dummy} + \text{Country Dummy} + \text{Stage Dummy} + \mu_i \quad (4)$$

To examine hypothesis 4, the variables of patent activity and interaction terms between patent activity and distance are added to each model above.

$$\text{Later stage} = e_0 + e_1\text{Distance} + e_2\text{Local Exp} + e_3\text{Local Exp*Distance} + e_4\text{Co-Investors} + e_5\text{VC Equity Amount} + e_6\text{CVC} + e_7\text{GVC} + e_8\text{VC Age}$$

$$+ e_9\text{VC Past Success} + e_{10}\text{Patent Activity}$$
$$+ e_{11}\text{Patent Activity} * \text{Distance Year Dummy} + \text{Country Dummy} \quad (5)$$

$$\text{Follow-on Funding} = f_0 + f_1\text{Distance} + f_2\text{Local Exp} + f_3\text{Local Exp*Distance}$$
$$+ f_4\text{Co-Investors} + f_5\text{VC Equity Amount} + f_6\text{CVC} + f_7\text{GVC}$$
$$+ f_8\text{VC Age} + f_9\text{VC Past Success} + f_{10}\text{Venture Age}$$
$$+ f_{11}\text{Patent Activity} + f_{12}\text{Patent Activity} * \text{Distance}$$
$$+ \text{Year Dummy} + \text{Country Dummy} + \text{Stage Dummy} + \mu_i \quad (6)$$

$$\text{Successful Exits} = g_0 + g_1\text{Distance} + g_2\text{Local Exp} + g_3\text{Local Exp*Distance}$$
$$+ g_4\text{Co-Investors} + g_5\text{VC Equity Amount} + g_6\text{CVC} + g_7\text{GVC}$$
$$+ g_8\text{VC Age} + g_9\text{VC Past Success} + g_{10}\text{Round Number}$$
$$+ g_{11}\text{Venture Age} + g_{12}\text{Patent Activity}$$
$$+ g_{13}\text{Patent Activity} * \text{Distance} + \text{Year Dummy}$$
$$+ \text{Country Dummy} + \text{Stage Dummy} + \mu_i \quad (7)$$

4. Sample and variables

Data is hand collected from the Thomson One database. Capital IQ and the company website are used to correct for missing data. For example, a portfolio firm may have missing data about equity amount or founded date in Thomson One but is available in Capital IQ or on the company website. The sample includes the first-time VC investment during the period 2010-2019. We only focus on the first financing round investment because most strategic decisions like deal evaluation and selection are made in this initial round and interactions with ventures in this strategic round create a foundation which is critical for ultimate success (Li et al., 2014). Moreover, we avoid using the follow-on rounds as VCs can learn from portfolio firms based on firm performance or outside environment and thus affect their investment decisions. Since it would be hard to capture all these potential factors, focusing on the first financing round allows us to reduce this bias. Using the first financing round is beneficial to this analysis as we cannot access financial information of portfolio firms. However, it would be quite normal for portfolio firms in this initial round to have negative operating and investing cash flows, financed by cash flow from financing activities. VCs will make investment decisions based on industry analysis and future development. Therefore, VCs will be less focused on or indifferent to the financial performance in the first round. In total, 790 biotechnological VC-backed firms are collected. As some countries in the sample only have one observation or their dependent variables do not change over time, they are automatically dropped using the logit model. However, controlling a country fixed effect is necessary because different countries possess different risks and financial conditions which drive the VC decision-making process. Eventually, the sample includes 774 observations and it is a cross-sectional dataset.[1]

4.1. Dependent variables

The first dependent variable is *later stage* which equals 1 if portfolio firms received VC investment at expansion or later stage and 0 otherwise. Then we create the two

[1] Hoenen et al. (2014) applied 586 US-based biotechnology firms over the period 2001-2010 empirically demonstrating the diminishing signalling effect of patent activity of portfolio firms.

dummy variables to represent VC-portfolio firm partnership performance: the likelihood of receiving *successful exits* and *follow-on funding*. Entrepreneurial firms will obtain the next VC financing only if they meet the milestones and have promising prospects. The survival to the next financing round is regarded as partnership success (Zhang and Gu, 2021). In addition, IPO and M&A are considered as successful exits. Empirical papers frequently adopt the two channels to measure the investment performance.

4.2. Independent variables

Consistent with Colombo et al. (2019), we measure *geographic distance* by using Google Maps Platform APIs. Geocoding provided by the service of the Geocoding API is a process of automatically converting addresses like cities into latitude and longitude coordinates. Then Google Maps Developer is applied to calculate the physical distance between the two cities that VC and the portfolio firms located based on the latitude and longitude information. Consistent with Cumming and Dai (2010), we measure the distance between headquarters of VCs and portfolio firms. Due to the skewness and nonlinearity of geographic distance, we take the natural logarithm of this variable.

In the context of syndication, lead VC is selected because they have stronger incentives to support and monitor portfolio firms. Lead VC is defined as the VC investors who acquire the largest equity amount. When there are two or more VC firms satisfying the criteria, we choose the closest one as they possess advantages in monitoring entrepreneurial firms and are typically assumed to take responsibility of oversight and consulting.

Local investment experience is the total number of investments a lead VC has made in the past three years in the portfolio firms' country. In our robustness checks, we also re-measure it based on all past investments.

4.3. Control variables

We first control group-level factors. The larger *number of co-investors* leads to conflicting viewpoints and interest misalignment, which will become an impediment to a long-term collaboration and an achievement of successful exits. *VC equity amount* represents the confidence about due diligence and expectations of future development of portfolio firms. A greater equity contribution also renders VCs to make more efforts to assist their portfolio firms and frequently interact with their peers. Portfolio firms receive the next financing round only if they reach the milestone, so the *number of financing rounds* is associated with the portfolio firms' development. More financing rounds also represent a higher level of monitoring intensity and the likelihood of receiving more resources from VCs, which ultimately promotes portfolio firms to achieve success. This variable is only used for testing hypothesis 2. Coordination risks are higher when there is a greater heterogeneity among VCs. Hence, we control two different types of VCs: a corporate VC (CVC) is controlled because they have different goals and structures such as longer investment durations compared to other VCs (Milosevic, 2018), while a governmental VC (GVC) may have a different focus (local investment preference) and target objectives (e.g. improving employment and economic development).

The characteristics of lead VCs are also important to the decision-making and eventual exits. *VC age* reflects the level of VC overall experience. A more experienced lead VC can be good at coordinating and maintaining relationships with other partners. Reputable VCs are able to overcome information asymmetries arising from geographic distance and exhibit a lower level of local bias (Cumming and Dai, 2010). *VC reputation* is the number of successful exits (IPO and M&A) the VC previously achieved.

Then we control portfolio firms' characteristics. The maturity of portfolio firms, often exhibited by *venture age*, is related to the level of uncertainty (Wang, 2017). Patent activities are also crucial for VC investment decision-making. We used Google Patent to gather the data about the number of *patent application*, *granted patent* and *patent citation* before VC investment. For example, if a VC firm invests in a portfolio firm in 2010, the number of patents is counted before 2010. Year and country dummies are also included. Table 1 lists the definition of variables.

5. Summary statistics

Table 2 displays the country distribution of portfolio firms. Almost half of portfolio firms in the sample are from the United States, followed by China and the United Kingdom, accounting for approximately 9.6% and 7.5% of the sample respectively.

Table 3 presents the descriptive statistics of variables. Although there are greater potential failure risks in the biotechnology industry, the majority of biotechnological ventures received their first VC financial injection at the early stage. On the one hand, early-stage ventures require a huge amount of money to design and develop their products. VC investments are essential to help them achieve success in R&D activities. On the other hand, VCs may pursue high-risk and high-reward investments. The sooner venture capitalists invest in an entrepreneurial firm, the more guidance or supports (both financial and human capital) they can provide. Consequently, portfolio firms may achieve better performance, while VCs are more likely to exit successfully. On average, around 20% of VC deals exit via either IPO or M&A, and 53% of portfolio firms obtain the follow-on funding.

Table 4 shows the correlation matrix. The correlation coefficient between venture age and later stage is 0.63 at the 1% significance level. The variable of venture age is dropped when we test for hypotheses 1 and 2. Round number is highly positively correlated with follow-on funding (0.69). However, this control variable will only be appropriate in examining the relationship between local investment experience and VC successful exits.

6. Empirical results

6.1. VC investment decisions

Since some countries in our sample either only have one observation or one outcome, using logit regression will predict success or failure perfectly after controlling country fixed effects. However, it is necessary to include country dummies as economic conditions and legal systems vary across different countries ultimately affecting investment decisions and outcomes. All regressions implement robust standard errors to control heteroskedasticity which is a common issue in cross-sectional data analysis. Average marginal effects instead of coefficient are reported.

Table 5 provides results to examine hypotheses 1 and 2. In column 1, the variable of distance is significantly positive indicating that distant VCs are more likely to invest in later-stage start-ups than closer VCs. The result verifies hypothesis 1. After adding the interaction terms between geographic distance and VC experience in column 2, distance still remains significantly positive. Moreover, we find that local experience enables distant VCs who are more likely to be involved in information-opaque entrepreneurial companies (i.e. early-stage ventures). The result is statistically significant and thus supports hypothesis 2. We also find that VCs with local experience are more likely to participate in the investment of early-stage ventures. Local experience benefits VCs due to the familiarity with business environments of local markets and the establishment of local networks, which improves due diligence and monitoring mechanisms.

In term of control variables, VCs are inclined to contribute less equity at an early stage because early-stage deals face higher risks. The results also show that VCs with higher past success rates increase the possibility of early-stage investment. This is because VCs become more experienced and professional from prior successful investments which allows them to explore riskier ventures.

6.2. VC-portfolio firm partnership performance

This section examines the moderating effect of local experience on the relationship between geographic distance and VC-portfolio firm partnership performance. *Follow-on funding* (a dummy variable equal to 1 if portfolio firms receive the follow-on funding from the initial lead VC and 0 otherwise) and *successful exits* (a dummy variable equal to 1 if VCs exit the investment via IPO or M&A and 0 otherwise) are implemented to proxy for partnership performance. Column 1 in table 6 displays whether local experience renders portfolio firms more likely to receive follow-on funding from distant VCs, while column 2 aims to investigate the moderating effect of local experience on the relationship between geographic distance and VC successful exits[2].

In table 6, geographic distance increases the likelihood of follow-on funding. Distant VCs could provide specific knowledge that is not locally available to support entrepreneurial firms' patent activities. They may conduct more thorough due diligence and better portfolio firms are selected through rigorous screening, which ultimately enhance the possibility of VC success. Furthermore, distant VCs may boost monitoring intensity through increasing financing round numbers and allocate less money to each round when they are located far away from portfolio firms. However, we do not find a significant negative moderating effect of local experience on the relationship between distance and follow-on funding. The number of co-investors is positively associated with the likelihood of receiving follow-on funding. Additionally, VC past success is beneficial to maintain successful partnership performance (i.e. more likely to achieve better exit performance and initiate the next financing round).

[2]The first two columns in panel B only include the year between 2010 and 2016 because the duration of VC investment is approximately five years. We leave the following five-year window to observe whether VCs exit via IPO or M&A.

In the second column the result does not support the idea that local experience means that VCs are more likely to achieve successful exits when they are farther away from portfolio firms. We find significant evidence that VC equity contribution at the initial round increases the likelihood of successful exits. Portfolio firms making use of greater amounts of paid-in capital to develop products and expand market are able to grow faster than peers. When investments involve GVC, exit performance becomes lower. Instead of improving portfolio firms' performance, GVC may also focus on the increase of employment opportunities and social welfare. We find a positive relationship between round number and VC successful exits. Prior successful investments render VC investors to provide high-quality value-added services and monitoring.

6.3. Signalling effect of patenting activity

The signalling quality of patenting activity is valuable to VC investment decisions due to the lack of track record of financial information at early-stage investment. This section aims to investigate whether patent activity of portfolio firms can reduce information frictions resulted from geographic distance. We adopt three different dimensions of patent activity (i.e. patent application, granted patents, and patent citation) that have been largely used to proxy for firms' innovation ability in empirical analysis. Ideally, higher levels of patent application, granted patents, and patent citation can send a positive signal to VC investors. To examine hypothesis 4, we incorporate the variables of patent activity and their interaction terms with distance in the model.

Table 7 identifies the moderating effect of patent activity on the relationship between distance and investment decision. However, we do not find significant results that distant VCs are more likely to invest in early-stage portfolio firms that possess patent applications, granted patents and patents cited by others before the first financing round. Later-stage portfolio firms are more likely to have patent activities. One possible reason is that patents take a long time to develop. When portfolio firms show successful patent activity, VCs can focus on the commercialisation of technological products in addition to the improvement of innovation ability which is a major task in the early stage. Furthermore, when portfolio firms show valuable patent activity, local VCs are more effective at capturing the investment opportunity compared to distant VCs. Therefore, although distant VC investors are willing to invest in the promising portfolio firms, they could be unable to compete with local VCs because of "local bias".

Tables 8 and 9 also show no significant results that patent activities are able to positively affect partnership performance in terms of distant VC investments. It is possible that VCs will only focus on the patents that have commercial value. Although some portfolio firms have patent activity before VC investment, VCs may find it meaningless or not valuable for firm development.

7. Endogeneity

Distance may not be an exogenous variable. The factors of geographic distance and stages of VC investment can be simultaneously considered in the VC decision-making process resulting in endogenous concerns. To tackle this issue, we use the IV approach by introducing an instrumental variable. Consistent with Tian (2011), the distance between the lead VC and the largest public company in portfolio firms' sector and country is selected as an instrument. The rationale behind this instrument is that being closer to the top companies in the same industry enhances the possibility of interacting with big market players and hence promoting portfolio firms' acquisitions. As it is expected that venture capitalists gain advantages from being closer to top companies in the industry, entrepreneurial firms may decide to locate near such VC investors, increasing the likelihood of getting acquired (relevance criterion). In addition, being geographically closer to the top companies should not be relevant to VC investment structure (exclusion restriction).

We use Google to search the biggest biotech companies in the portfolio firms' country, and these are selected based on their market capitalisation at the end of the year. As our dependent variable is a dummy, the use of the IV-probit model is appropriate. Table 10 lists the regression results of the IV-probit method. The first and second columns are the first and second stages respectively. The instrumental variable is significantly positive and consistent with the argument of Tian (2011). However, in the second stage, the variable of distance has no significant influence on later-stage investment decisions. The Wald test of exogeneity has the P-value of 0.138 indicating that we cannot reject the null hypothesis of no endogeneity. In other words, there is no need to use the IV approach. Columns 3-4 add the interaction term. The result suggests local experience has no moderating effects on geographic distance and later stage after correcting endogeneity.

8. Robustness checks

We conduct several tests to determine whether our results are robust or not. First, we use an alternative measure for the variable of local experience which is measured based on the investments in the past. Our results still remain very similar (see tables 1-5 in appendix).

Second, since the majority of VC firms have investment experience in the domestic market, we further use same city experience as an alternative measure of local experience. It equals 1 if the lead VC firm previously invested in the city where the entrepreneurial company located and 0 otherwise. Table 6 in the appendix shows that when VCs possess the same city experience they are less likely to finance later-stage portfolio firms than early-stage ones. Instead, they are able to capture early-stage investment opportunities. Furthermore, the same city experience has a negative moderating effect on the relationship between later-stage investment and geographic distance indicating that distant VCs that previously made investments in the same city as the present ones are more likely to invest in early-stage portfolio firms. It is also noticeable that same city experience has stronger impacts on investment decisions than local experience. Table 7 in the appendix demonstrates that same city experience benefits distant VCs from building a successful partnership with portfolio firms. Namely, when distant VCs have prior investment experience in the same city as portfolio firms, they are more likely to participate in the follow-on funding and achieve successful future exits.

Third, we replace geographic distance with a dummy indicating whether a lead VC is international or not. The dummy variable of international VC is not significant through all regressions (tables 11-15). One explanation of why international VCs have no significant influence on investment decisions is that geographic distance is just one of the factors they would consider. Since we focus on the biotechnology industry, international VCs could strategically invest in early-stage portfolio firms to pursue higher returns. However, we find that with local experience, international VCs are less likely to invest in later-stage ventures. International VCs may bring unique resources so they may play a crucial role in the success of young ventures. This is also confirmed by our empirical evidence suggesting that foreign VCs positively affect VC-portfolio firm partnership performance, although the results are not significant.

Fourth, we examine the impacts of geographic distance on VC investments across emerging and developed economies. Our results in table 16 show that in the emerging markets, geographic distance has no significant impact on VC investment decisions, whereas there is a significantly positive relationship between geographic distance and VC investment decisions in the developed markets. Since the developed markets possess more mature legal and financial systems, portfolio firms have to adhere to strict industry standards and tend to be well regulated. Better economic environments enable VC investors to conduct better due diligence and suffer less from the problems of moral hazard. By contrast, VC investments are associated with higher risks when investing in emerging economies (Nahata et al., 2014). We also find that local investment experience enables distant VCs to make early-stage investment decisions in the emerging market but not in the developed markets, indicating that local experience is more valuable for VC investors in emerging economies. However, in terms of the relationship between geographic distance and investment outcomes in the two different contexts, the results in table 17 remain very similar as previous ones in table 6. We only find that geographic distance is positively related to follow-on funding in both emerging and developed markets.

9. Discussion and conclusion

This paper investigates the moderating effects of local investment experience on distant VC investment based on the evidence from the biotechnology industry. Distant VCs encounter greater risks as geographic distance is related to higher information costs and asymmetries. Geographic proximity benefits VCs from conducting thorough due diligence and monitoring portfolio firms. Hence, distance between VCs and portfolio firms affects VC investment decisions. We find that distant investments are associated with a lower likelihood of later-stage investment. Moreover, local investment experience makes distant VC investors more likely to finance early-stage ventures. We further examine the moderating effect of local experience on the relationship between geographic distance and VC-portfolio firm partnership performance (i.e. the likelihood of receiving follow-on funding and achieving successful exits). However, we do not find that local experience positively moderates the effects of geographic distance on partnership performance.

Patent activity has a signalling effect (Hoenen et al., 2014). Distant VCs could be attracted by high-quality entrepreneurial firms that have patent applications, granted patents, or patents cited by others. These patent activities increase the transparency of portfolio firms. Our results suggest that patent activities are positively associated with later-stage investments. It is reasonable because patents are time-consuming and later-stage ventures possess more patents. However, we do not find significant evidence that patent activities attract distant VCs to invest in early-stage ventures and help VCs achieve successful partnership performance. On the one hand, VCs may assess the quality of patent activities. Although early-stage firms with patent activity are able to send a positive signal to venture capitalists, the commercialisation and future success still remain uncertain. On the other hand, it might be difficult for distant VCs to access these promising ventures due to "local bias".

Two robustness checks are also implemented. We first use an alternative measure for local experience based on all past investments. Our results remain very similar. Second, we replace geographic distance with international VCs. We only find that local experience is helpful for international VCs to make early-stage investment decisions. The insignificant results demonstrate that geographic distance might be only one of the factors foreign VCs will consider.

We conducted additional analysis which aims to examine the effect of same city experience. Our findings show that same city experience enhances the possibility of distant VCs to invest in early-stage ventures, participate in the follow-on funding, and achieve successful exits. Furthermore, it has stronger impacts on investment decisions and partnership performance compared to local experience. VCs could be more familiar with local environment and more likely to establish local networks reducing monitoring costs when they previously made investments in the same city as portfolio firms.

The empirical evidence has several implications in practice, both for VCs and portfolio firms. Although geographic distance poses higher investment costs and risks, VC investors can absorb knowledge from local investments. Distant VCs can increase their risk attitudes through local investment experience. Additionally, distant VCs that are relatively risk-averse could focus on the investment opportunities in the areas that they previously invested before. When VCs are located far away from portfolio firms and have less local experience, they could syndicate with other VCs (e.g. local VCs) who are more familiar with the local environment. Portfolio firms could benefit from distant VC investments. Due to information asymmetries, VCs may increase their monitoring intensity to help portfolio firms meet the milestones so that they are more likely to raise the follow-on funds. Moreover, early-stage ventures could seek funding from distant VCs that have more local investment experience to obtain the resources that are not locally available. Entrepreneurial firms should link patent activity closely with firm future development in order to attract distant VC investments.

This research is not without limitations. We do not incorporate financial performance of portfolio firms. Future research could incorporate the factors of firm performance in the analysis. This study only focuses on the biotechnology industry; the question of whether the effect of local experience can be generalised in other industries still remains unknown. In addition, the measurement of geographic distance could be biased by the fact that some VC firms may have local offices. However, the information about local offices is not available.

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Tables

Table 1: Definition of variables

Dependent variables:	Definition	Data sources:
Later stage	A dummy variable equals 1 if portfolio firms received VC investment at expansion or later stage and 0 otherwise.	Thomson One
Successful exits	A dummy variable equals 1 if VCs exit the investment via IPO or M&A and 0 otherwise.	Thomson One
Follow-on funding	A dummy variable equals 1 if portfolio firms receive the follow-on funding from the initial lead VC and 0 otherwise.	Thomson One
Independent variables:		
Distance	The natural logarithm of the geographic distance between lead VC and portfolio firms.	Google Maps Platform APIs
Local exp	The natural logarithm of total number of investments a lead VC has made in the portfolio firm's country in the past three years.	Thomson One
Co-investors	The natural logarithm of total number of VC investors in the first financing round.	Thomson One
VC equity amount	The natural logarithm of total equity amount of portfolio firms received in the first financing round.	Thomson One, Capital IQ, company website
Round number	The natural logarithm of total number of financing round(s).	Thomson One
CVC	A dummy variable equals 1 if the lead VC is a corporate VC and 0 otherwise.	Thomson One
GVC	A dummy variable equals 1 if the lead VC is a governmental VC and 0 otherwise.	Thomson One
VC age	The natural logarithm of VC firms' age which is the difference between VC founded year and the fiscal year.	Thomson One
VC past success	The total number of successful exits (IPO and M&A) the lead VC previously achieved divided by the total number of investments in the past.	Thomson One
Venture age	The natural logarithm of portfolio firms' age which is the difference between portfolio firms' founded year and the fiscal year.	Thomson One, Capital IQ
Patent application	The natural logarithm of the number of portfolio firms' patent applications before VC investment.	Google Patent
Granted patent	The natural logarithm of the number of portfolio firms' granted patents before VC investment.	Google Patent
Patent citation	The natural logarithm of the number of portfolio firms' patents cited by other firms before VC investment.	Google Patent

Table 2: Country distribution of portfolio firms

Countries	Obs.
Australia	11
Belgium	8
Brazil	7
Canada	26
China	74
Denmark	8
Finland	3
France	53
Germany	19
Hungary	2
India	11
Ireland	11
Israel	14
Italy	6
Japan	7
Netherlands	8
Norway	3
Poland	2
Russia	3
Spain	14
Sweden	6
Switzerland	15
United Kingdom	58
United States	405
Total	774

Table 3: Summary statistics

Variables	Obs.	Mean	S.D	Min	Max
Later stage	774	0.297	0.457	0	1
Successful exits	774	0.200	0.400	0	1
Follow-on funding	774	0.527	0.500	0	1
Distance (*miles*)	774	1092.205	1909.866	0	8443.39
Local exp	774	1.852	1.324	0	4.963
Co-investors	774	2.333	1.705	1	13
VC equity amount *($ Mil*)	774	12.408	22.746	0.01	251
Round number	774	2.783	2.216	1	15
CVC	774	0.110	0.313	0	1
GVC	774	0.076	0.266	0	1
VC age	774	15.849	14.193	0	116
VC past success	774	0.305	0.272	0	1
Venture age	774	3.747	4.520	0	34
Patent application	774	0.569	0.857	0	4.673
Granted patent	774	0.224	0.583	0	4.673
Patent citation	774	0.177	0.708	0	5.717

Table 4: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
1) Later stage	1.00															
2) Successful exits	-0.06	1.00														
3) Follow-on funding	-0.25*	0.13	1.00													
4) Distance	0.07	0.14	0.13	1.00												
5) Local exp	-0.24*	0.06	0.10	-0.10	1.00											
6) Co-investors	0.01	0.08	0.18*	0.08	0.02	1.00										
7) VC equity amount	0.11	0.23*	0.10	0.22*	-0.06	0.45*	1.00									
8) Round number	-0.22*	0.22*	0.69*	0.10	0.12	0.10	0.04	1.00								
9) CVC	-0.04	0.01	0.03	0.15*	-0.09	0.10	0.16*	0.01	1.00							
10) GVC	-0.04	-0.11	-0.04	-0.16*	0.27*	-0.13	-0.31*	-0.05	-0.10	1.00						
11) VC age	-0.15*	0.09	0.15*	0.07	0.46*	0.10	0.07	0.14*	-0.04	0.11	1.00					
12) VC past success	-0.13*	0.28*	0.26*	0.12	0.21*	0.03	0.26*	0.31*	0.08	-0.13	0.34*	1.00				
13) Venture age	0.63*	-0.04	-0.23*	0.08	-0.16*	-0.01	0.08	-0.24*	-0.03	-0.02	-0.08	-0.13	1.00			
14)Patent application	0.34*	0.04	-0.01	0.08	-0.16*	0.10	0.19*	0.04	0.01	-0.05	-0.05	0.01	0.34*	1.00		
15)Granted patent	0.32*	0.03	-0.09	0.09	-0.12	0.08	0.18*	-0.02	0.03	-0.08	-0.04	-0.01	0.29*	0.76*	1.00	
16)Patent citation	0.23*	0.05	-0.03	0.05	-0.01	0.07	0.12	0.06	0.04	-0.05	0.02	0.07	0.22*	0.50*	0.72*	1.00

Note: * shows significance at the 0.01 level.

Table 5

Logit regressions are conducted to analyse whether distant VC investments are more likely to invest in early-stage ventures and whether local experience can help VCs overcome geographic distance to invest in early-stage ventures. The dependent variable of *later stage* is a dummy variable that equals 1 if portfolio firms received VC investment at seed or early stage and 0 otherwise. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Later stage	(2) Later stage
Distance	0.012**	0.011**
	(2.19)	(2.06)
Local exp	-0.067***	-0.066***
	(-4.65)	(-4.57)
Distance*Local exp		-0.008**
		(-1.99)
Co-investors	0.002	0.003
	(0.08)	(0.11)
VC equity amount	0.043***	0.042***
	(3.84)	(3.81)
CVC	-0.096	-0.066
	(-1.38)	(-1.33)
GVC	0.106	0.097
	(1.55)	(1.44)
VC age	-0.004	-0.005
	(-0.17)	(-0.23)
VC past success	-0.118*	-0.116*
	(-1.80)	(-1.76)
Year dummy	YES	YES
Country dummy	YES	YES
Pseudo R^2	18.81%	19.01%
Log pseudolikelihood	-382.327	-381.417
N	774	774

Table 6

This table investigates the moderating effect of local experience on the relationship between geographic distance and VC-portfolio firm partnership performance. The dependent variable in the first two columns is *successful exits* which is a dummy variable equal to 1 if VCs exit the investment via IPO or M&A and 0 otherwise, while the last two columns use *follow-on funding* as a dependent variable which equals to 1 if portfolio firms receive the follow-on funding from the initial lead VC and 0 otherwise. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance levels respectively.

	(1) Follow-on funding	(2) Successful exits
Distance	0.017***	0.011
	(2.90)	(1.59)
Local exp	0.008	0.003
	(0.55)	(0.18)
Distance*Local exp	-0.002	-0.005
	(-0.46)	(-0.77)
Co-investors	0.120***	0.022
	(3.93)	(0.65)
VC equity amount	0.003	0.043***
	(0.26)	(2.73)
CVC	-0.095	-0.077
	(-1.64)	(-1.37)
GVC	-0.002	-0.239*
	(-0.03)	(-1.85)
VC age	-0.002	-0.003
	(-0.07)	(-0.09)
VC past success	0.278***	0.189**
	(3.49)	(2.48)
Venture age	-0.027	-0.002
	(-0.96)	(-0.06)
Round number		0.056*
		(1.81)
Year dummy	YES	YES
Country dummy	YES	YES
Stage dummy	YES	YES
Pseudo R^2	17.03%	20.79%
Log pseudolikelihood	-428.649	-204.986
N	747	453

Table 7

This table reports the results of the signalling effect of portfolio firms' patent activity. The dependent variable of *laterstage* is a dummy variable that equals 1 if portfolio firms received VC investment at seed or early stage and 0 otherwise. Three dimensions of patent activity are adopted as new independent variables. Patent application, granted patent and patent citation take the natural logarithm of the number of portfolio firms' patent applications, granted patents and patent citation respectively before VC investment.Control variables are previously used and definitions are in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Later stage	(2) Later stage	(3) Later stage
Distance	0.009*	0.008*	0.010**
	(1.87)	(1.70)	(2.06)
Local exp	-0.048***	-0.053***	-0.063***
	(-3.62)	(-3.92)	(-4.68)
Distance*Local exp	-0.007*	-0.005	-0.006
	(-1.79)	(-1.34)	(-1.60)
Co-investors	-0.006	-0.001	-0.008
	(-0.24)	(-0.02)	(-0.34)
VC equity amount	0.027**	0.031***	0.036***
	(2.49)	(2.97)	(3.44)
CVC	-0.054	-0.069	-0.082
	(-1.17)	(-1.40)	(-1.55)
GVC	0.070	0.100	0.110*
	(1.09)	(1.64)	(1.75)
VC age	-0.012	-0.011	-0.004
	(-0.65)	(-0.58)	(-0.21)
VC past success	-0.108*	-0.102	-0.124**
	(-1.69)	(-1.63)	(-2.03)
Patent application	0.130***		
	(8.68)		
Patent application*	0.000		
Distance	(0.08)		
Granted patent		0.183***	
		(7.39)	
Granted patent*		0.008	
Distance		(1.05)	
Patent citation			0.136***
			(6.32)
Patent citation*			0.011
Distance			(1.26)
Year dummy	YES	YES	YES
country dummy	YES	YES	YES
Pseudo R^2	25.67%	25.31%	24.56%
Log pseudolikelihood	-350.049	-351.725	-355.254
N	774	774	774

Table 8

This table reports the results of signalling effect of portfolio firms' patent activity. Three dimensions of patent activity are adopted as new independent variables.*Follow-on funding* is used as a dependent variable which equals 1 if portfolio firms receive the follow-on funding from the initial lead VC and 0 otherwise. Patent application, granted patent and patent citation take the natural logarithm of the number of portfolio firms' patent applications, granted patents and patent citation respectively before VC investment. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Follow-on funding	(2) Follow-on funding	(3) Follow-on funding
Distance	0.017***	0.017***	0.017***
	(2.83)	(2.97)	(2.89)
Local exp	0.010	0.008	0.009
	(0.66)	(0.53)	(0.57)
Distance*Local exp	-0.003	-0.002	-0.002
	(-0.59)	(-0.46)	(-0.47)
Co-investors	0.117***	0.121***	0.120***
	(3.85)	(3.96)	(3.91)
VC equity amount	0.002	0.004	0.004
	(0.13)	(0.31)	(0.30)
CVC	-0.091	-0.095	-0.117**
	(-1.56)	(-1.64)	(-2.41)
GVC	-0.006	-0.004	-0.086
	(-0.09)	(-0.06)	(-1.52)
VC age	-0.003	0.000	0.009
	(-0.14)	(0.00)	(0.37)
VC past success	0.278***	0.276***	0.261***
	(3.48)	(3.46)	(3.31)
Venture age	-0.033	-0.024	-0.030
	(-1.17)	(-0.87)	(-1.04)
Patent application	0.038*		
	(1.77)		
Patent application* Distance	-0.007		
	(-0.78)		
Granted patent		-0.037	
		(-1.18)	
Granted patent* Distance		0.006	
		(0.49)	
Patent citation			0.027
			(0.43)
Patent citation* Distance			0.004
			(0.46)
Year dummy	YES	YES	YES
Country dummy	YES	YES	YES
Stage dummy	YES	YES	YES
Pseudo R^2	17.33%	17.15%	17.07%
Log pseudolikelihood	-427.102	-428.037	-428.488
N	747	747	747

Table 9

This table reports the results of signalling effect of portfolio firms' patent activity. Three dimensions of patent activity are adopted as new independent variables. The dependent variable is *successful exits* which is a dummy variable equal to 1 if VCs exit the investment via IPO or M&A and 0 otherwise. Patent application, granted patent and patent citation take the natural logarithm of the number of portfolio firms' patent applications, granted patents and patent citation respectively before VC investment. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Successful exits	(2) Successful exits	(3) Successful exits
Distance	0.011	0.011	0.011
	(1.60)	(1.61)	(1.54)
Local exp	0.003	0.004	0.001
	(0.16)	(0.20)	(0.07)
Distance*Local exp	-0.005	-0.005	-0.004
	(-0.75)	(-0.78)	(-0.63)
Co-investors	0.026	0.022	0.025
	(0.75)	(0.66)	(0.75)
VC equity amount	0.044***	0.043***	0.040**
	(2.75)	(2.73)	(2.53)
CVC	-0.077	-0.078	-0.073
	(-1.36)	(-1.38)	(-1.29)
GVC	-0.236*	-0.240*	-0.246*
	(-1.82)	(-1.84)	(-1.86)
VC age	-0.003	-0.002	-0.005
	(-0.09)	(-0.08)	(-0.19)
VC past success	0.190**	0.189**	0.200***
	(2.49)	(2.47)	(2.62)
Venture age	-0.000	-0.002	-0.003
	(-0.01)	(-0.05)	(-0.09)
Round number	0.058*	0.057*	0.056*
	(1.86)	(1.82)	(1.80)
Patent application	-0.017		
	(-0.75)		
Patent application* Distance	-0.001		
	(-0.09)		
Granted patent		-0.010	
		(-0.29)	
Granted patent* Distance		0.002	
		(0.12)	
Patent citation			0.005
			(0.22)
Patent citation* Distance			-0.014
			(-1.58)
Year dummy	YES	YES	YES
Country dummy	YES	YES	YES
Stage dummy	YES	YES	YES
Pseudo R^2	20.89%	20.80%	21.12%
Log pseudolikelihood	-204.709	-204.950	-204.126
N	453	453	453

Table 10

This table shows the regression results of IV-probit model. The instrument is the distance between lead VC and the largest biotech company in the portfolio firms' country. The dependent variable of *laterstage* is a dummy variable that equals 1 if portfolio firms received VC investment at seed or early stage and 0 otherwise. Control variables are previously used and definitions are in table 1. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Distance	(2) Later stage	(3) Distance	(4) Later stage
Instrument	0.435***	-0.050	0.235***	-0.119
	(8.20)	(-0.74)	(6.95)	(-0.93)
Local exp	-0.149	-0.274***	- 1.672***	-0.502**
	(-1.62)	(-4.95)	(-22.78)	(-2.06)
Instrument*Local exp			0.346***	0.051
			(33.65)	(1.07)
Co-investors	-0.179	-0.005	-0.176	-0.021
	(-1.03)	(-0.05)	(-1.62)	(-0.21)
VC equity amount	0.220***	0.183***	0.114**	0.183***
	(3.05)	(3.96)	(2.51)	(3.95)
CVC	0.657**	-0.169	0.131	-0.205
	(2.02)	(-0.87)	(0.64)	(-1.08)
GVC	-0.410	0.334	0.440*	0.432*
	(-0.97)	(1.38)	(1.66)	(1.73)
VC age	0.276**	0.012	0.211**	0.021
	(2.03)	(0.16)	(2.48)	(0.27)
VC past success	0.289	-0.414*	-0.009	-0.447*
	(0.65)	(-1.73)	(-0.03)	(-1.84)
Constant	0.939*	0.099	2.948***	0.466
	(1.70)	(0.29)	(8.41)	(0.76)
Year dummy	YES	YES	YES	YES
Country dummy	YES	YES	YES	YES
F-statistics	5.27		40.68	
Adj-R^2	18.09%		67.79%	
Wald test of exogeneity (p-value)		0.138		0.121
N	774	774	774	774

Table 11

Robustness checks by replacing geographic distance with a dummy variable of *international VC*. The dependent variable of *laterstage* is a dummy variable that equals 1 if portfolio firms received VC investment at seed or early stage and 0 otherwise. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Later stage	(2) Later stage
International VC	0.009	-0.039
	(0.21)	(-1.02)
Local exp	-0.070***	-0.076***
	(-4.72)	(-5.05)
International VC *Local exp		-0.055***
		(-3.41)
Co-investors	-0.000	-0.003
	(-0.01)	(-0.12)
VC equity amount	0.047***	0.047***
	(4.22)	(4.23)
CVC	-0.060	-0.046
	(-1.12)	(-0.86)
GVC	0.098	0.082
	(1.46)	(1.25)
VC age	0.001	0.003
	(0.03)	(0.16)
VC past success	-0.118*	-0.125*
	(-1.80)	(-1.90)
Year dummy	YES	YES
Country dummy	YES	YES
Pseudo R^2	18.31%	19.34%
Log pseudolikelihood	-384.724	-379.850
N	774	774

Table 12

Robustness checks by replacing geographic distance with a dummy variable of *international VC*. The dependent variable in the first column uses *follow-on funding* as a dependent variable which equals 1 if portfolio firms receive the follow-on funding from the initial lead VC and 0 otherwise, while the second column is a dummy variable that equals 1 if VCs exit the investment via IPO or M&A and 0 otherwise. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Follow-on funding	(2) Successful exits
International VC	0.010	0.034
	(0.17)	(0.52)
Local exp	0.006	0.000
	(0.35)	(0.02)
International VC *Local exp	0.016	0.006
	(0.98)	(0.32)
Co-investors	0.116***	0.021
	(3.78)	(0.61)
VC equity amount	0.007	0.046***
	(0.59)	(2.95)
CVC	-0.081	-0.073
	(-1.33)	(-1.20)
GVC	-0.018	-0.248*
	(-0.28)	(-1.96)
VC age	0.002	0.003
	(0.08)	(0.09)
VC past success	0.271***	0.176**
	(3.40)	(2.30)
Venture age	-0.025	0.003
	(-0.87)	(0.08)
Round number		0.061*
		(1.96)
Year dummy	YES	YES
Country dummy	YES	YES
Stage dummy	YES	YES
Pseudo R^2	16.53%	20.37%
Log pseudolikelihood	-431.276	-206.062
N	747	453

Table 13

Robustness checks by replacing geographic distance with a dummy variable of *international VC*. The dependent variable of *laterstage* is a dummy variable that equals 1 if portfolio firms received VC investment at seed or early stage and 0 otherwise. Three dimensions of patent activity are adopted as new independent variables. Patent application, granted patent and patent citation take the natural logarithm of the number of portfolio firms' patent applications, granted patents and patent citation respectively before VC investment. Control variables are previously used and definitions are in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Later stage	(2) Later stage	(3) Later stage
International VC	-0.027	-0.044	-0.038
	(-0.74)	(-1.34)	(-0.99)
Local exp	-0.057***	-0.064***	-0.074***
	(-4.12)	(-4.56)	(-5.12)
International VC*Local exp	-0.036**	-0.043***	-0.054***
	(-2.42)	(-2.86)	(-3.56)
Co-investors	-0.012	-0.006	-0.011
	(-0.48)	(-0.25)	(-0.44)
VC equity amount	0.031***	0.036***	0.040***
	(2.90)	(3.41)	(3.79)
CVC	-0.036	-0.048	-0.059
	(-0.75)	(-0.92)	(-1.07)
GVC	0.058	0.085	0.093
	(0.93)	(1.43)	(1.52)
VC age	-0.006	-0.005	0.001
	(-0.31)	(-0.24)	(0.06)
VC past success	-0.117*	-0.111*	-0.131**
	(-1.82)	(-1.76)	(-2.11)
Patent application	0.130***		
	(8.70)		
Patent application*	0.133***		
International VC	(8.28)		
Granted patent		0.188***	
		(7.50)	
Granted patent*		0.188***	
International VC		(7.18)	
Patent citation			0.134***
			(6.85)
Patent citation*			0.140***
International VC			(6.34)
Year dummy	YES	YES	YES
country dummy	YES	YES	YES
Pseudo R^2	26.10%	25.83%	24.72%
Log pseudolikelihood	-348.024	-349.275	-354.498
N	774	774	774

Table 14

Robustness checks by replacing geographic distance with a dummy variable of *international VC*. Three dimensions of patent activity are adopted as new independent variables. *Follow-on funding* is used as a dependent variable which equals 1 if portfolio firms receive the follow-on funding from the initial lead VC and 0 otherwise. Patent application, granted patent and patent citation take the natural logarithm of the number of portfolio firms' patent applications, granted patents and patent citation respectively before VC investment. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Follow-on funding	(2) Follow-on funding	(3) Follow-on funding
International VC	0.011	0.009	0.009
	(0.18)	(0.15)	(0.15)
Local exp	0.007	0.005	0.006
	(0.43)	(0.33)	(0.40)
International VC *Local exp	0.019	0.015	0.016
	(1.19)	(0.94)	(1.01)
Co-investors	0.114***	0.117***	0.115***
	(3.77)	(3.81)	(3.75)
VC equity amount	0.005	0.008	0.008
	(0.40)	(0.63)	(0.65)
CVC	-0.070	-0.082	-0.090
	(-1.14)	(-1.33)	(-1.47)
GVC	-0.021	-0.020	-0.020
	(-0.32)	(-0.31)	(-0.31)
VC age	0.001	0.003	0.004
	(0.05)	(0.12)	(0.15)
VC past success	0.271***	0.271***	0.272***
	(3.44)	(3.38)	(3.38)
Venture age	-0.028	-0.023	-0.025
	(-0.99)	(-0.81)	(-0.90)
Patent application	0.041*		
	(1.92)		
Patent application* International VC	0.056** (2.46)		
Granted patent		-0.030	
		(-0.94)	
Granted patent* International VC		-0.034 (-0.97)	
Patent citation			-0.009
			(-0.39)
Patent citation* International VC			-0.028 (-1.04)
Year dummy	YES	YES	YES
Country dummy	YES	YES	YES
Stage dummy	YES	YES	YES
Pseudo R^2	17.16%	16.61%	16.82%
Log pseudolikelihood	-428.014	-430.821	-429.742
N	747	747	747

Table 15

Robustness checks by replacing geographic distance with a dummy variable of *international VC*. Three dimensions of patent activity are adopted as new independent variables. The dependent variable is *successful exits* which is a dummy variable equal to 1 if VCs exit the investment via IPO or M&A and 0 otherwise. Patent application, granted patent and patent citation take the natural logarithm of the number of portfolio firms' patent applications, granted patents and patent citation respectively before VC investment. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Successful exits	(2) Successful exits	(3) Successful exits
International VC	0.032	0.032	0.036
	(0.48)	(0.49)	(0.55)
Local exp	-0.001	0.001	-0.000
	(-0.04)	(0.05)	(-0.00)
International VC *Local exp	0.006	0.006	0.006
	(0.29)	(0.32)	(0.31)
Co-investors	0.024	0.021	0.021
	(0.71)	(0.64)	(0.61)
VC equity amount	0.047***	0.046***	0.046***
	(2.98)	(2.91)	(2.92)
CVC	-0.070	-0.075	-0.071
	(-1.14)	(-1.24)	(-1.17)
GVC	-0.246*	-0.247*	-0.248*
	(-1.95)	(-1.95)	(-1.95)
VC age	0.003	0.002	0.002
	(0.11)	(0.09)	(0.07)
VC past success	0.177**	0.178**	0.176**
	(2.30)	(2.32)	(2.28)
Venture age	0.006	0.002	0.003
	(0.15)	(0.05)	(0.09)
Round number	0.062**	0.061**	0.062**
	(1.98)	(1.96)	(1.97)
Patent application	-0.015		
	(-0.63)		
Patent application* International VC	-0.011 (-0.43)		
Granted patent		-0.006	
		(-0.17)	
Granted patent* International VC		-0.014 (-0.38)	
Patent citation			-0.002
			(-0.06)
Patent citation* International VC			0.005 (0.18)
Year dummy	YES	YES	YES
Country dummy	YES	YES	YES
Stage dummy	YES	YES	YES
Pseudo R^2	20.47%	20.44%	20.44%
Log pseudolikelihood	-205.806	-205.889	-205.878
N	453	453	453

Table 16
This table examines the relationship between geographic distance and later-stage investment decisions in emerging and developed markets respectively. The dependent variable of *laterstage* is a dummy variable equal to 1 if portfolio firms received VC investment at seed or early stage and 0 otherwise. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	Emerging market		Developed market	
	(1)	(2)	(3)	(4)
	Later stage	Later stage	Later stage	Later stage
Distance	-0.021	-0.023	0.017***	0.016***
	(-1.32)	(-1.48)	(2.88)	(2.82)
Local exp	-0.079**	-0.076*	-0.062***	-0.061***
	(-2.10)	(-1.87)	(-3.92)	(-3.90)
Distance*Local exp		-0.031**		-0.007
		(-2.09)		(-1.56)
Co-investors	-0.029	-0.011	0.003	0.004
	(-0.35)	(-0.15)	(0.13)	(0.15)
VC equity amount	0.090**	0.091***	0.037***	0.037***
	(2.43)	(2.64)	(3.12)	(3.11)
CVC	-0.184	-0.142	-0.032	-0.031
	(-0.98)	(-0.71)	(-0.66)	(-0.64)
GVC	0.183	0.189	0.101	0.097
	(0.83)	(0.95)	(1.45)	(1.39)
VC age	0.065	0.079	-0.007	-0.007
	(0.91)	(1.10)	(-0.34)	(-0.37)
VC past success	-0.164	0.198	-0.165**	-0.165**
	(-0.75)	(1.01)	(-2.24)	(-2.24)
Year dummy	YES	YES	YES	YES
Country dummy	YES	YES	YES	YES
Pseudo R^2	17.74%	21.96%	16.25%	16.29%
Log pseudolikelihood	-51.855	-39.192	-320.440	-320.294
N	95	95	677	677

Table 17
This table examines the relationship between geographic distance and investment outcomes in emerging and developed markets respectively. The dependent variable of *stage* is a dummy variable that equals 1 if portfolio firms received VC investment at seed or early stage and 0 otherwise. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	Emerging market		Developed market	
	(1) Follow-on funding	(2) Successful exits	(3) Follow-on funding	(4) Successful exits
Distance	0.065*	0.006	0.015**	0.009
	(1.80)	(0.36)	(2.38)	(1.14)
Local exp	0.053	-0.016	0.007	0.010
	(1.42)	(-0.18)	(0.43)	(0.51)
Distance*Local exp	0.001	-0.015	-0.001	-0.003
	(0.03)	(-0.89)	(-0.19)	(-0.47)
Co-investors	0.325***	-0.358***	0.091***	0.043
	(3.97)	(-3.13)	(2.73)	(1.24)
VC equity amount	-0.096	0.071	0.011	0.050***
	(-1.43)	(1.43)	(0.86)	(2.91)
CVC	-0.134	-0.225	-0.120*	-0.080
	(-0.82)	(-0.78)	(-1.92)	(-1.28)
GVC	0.209	Omitted	-0.013	-0.341**
	(1.43)		(-0.19)	(-2.11)
VC age	-0.100**	0.034	0.004	-0.003
	(-2.12)	(0.33)	(0.14)	(-0.10)
VC past success	-0.044	0.374*	0.284**	0.141*
	(-0.91)	(1.66)	(3.12)	(1.73)
Venture age	-0.044	-0.100	-0.016	0.005
	(-0.91)	(-0.82)	(-0.54)	(0.11)
Round number		0.092		0.039
		(0.56)		(1.27)
Year dummy	YES	YES	YES	YES
Country dummy	YES	YES	YES	YES
Pseudo R^2	55.84%	36.53%	14.92%	22.98%
Log pseudolikelihood	-19.207	-17.707	-386.662	-175.825
N	75	45	662	404

Appendix

Table 1

Robustness checks for table 5 use an alternative measure for VC local experience based on all past investments. The dependent variable of *laterstage* is a dummy variable that equals 1 if portfolio firms received VC investment at seed or early stage and 0 otherwise. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(2) Later stage	(4) Later stage
Distance	0.010*	0.009*
	(1.90)	(1.77)
Local exp	-0.071***	-0.071***
	(-6.27)	(-6.24)
Distance*Local exp		-0.006**
		(-2.00)
Co-investors	0.003	0.004
	(0.10)	(0.18)
VC equity amount	0.041***	0.041***
	(3.71)	(3.67)
CVC	-0.073	-0.072
	(-1.47)	(-1.45)
GVC	0.115*	0.105
	(1.72)	(1.61)
VC age	0.026	0.025
	(1.24)	(1.20)
VC past success	-0.060	-0.059
	(-0.93)	(-0.92)
Year dummy	YES	YES
Country dummy	YES	YES
Pseudo R^2	20.33%	20.49%
Log pseudolikelihood	-375.206	-374.435
N	774	774

Table 2

Robustness checks for table 6 use an alternative measure for VC local experience based on all past investments. The first column uses *follow-on funding* as a dependent variable which equals 1 if portfolio firms receive the follow-on funding from the initial lead VC and 0 otherwise, while the second column is a dummy variable equal to 1 if VCs exit the investment via IPO or M&A and 0 otherwise. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Follow-on funding	(2) Successful exits
Distance	0.018***	0.011
	(3.01)	(1.50)
Local exp	0.018	-0.002
	(1.41)	(-0.14)
Distance*Local exp	-0.002	-0.004
	(-0.40)	(-0.82)
Co-investors	0.119***	0.023
	(3.92)	(0.67)
VC equity amount	0.003	0.043***
	(0.28)	(2.71)
CVC	-0.094	-0.079
	(-1.62)	(-1.42)
GVC	-0.014	-0.238*
	(-0.21)	(-1.82)
VC age	-0.015	0.002
	(-0.58)	(0.08)
VC past success	0.259**	0.191**
	(3.21)	(2.53)
Venture age	-0.027	-0.002
	(-0.97)	(-0.06)
Round number		0.057*
		(1.85)
Year dummy	YES	YES
Country dummy	YES	YES
Stage dummy	YES	YES
Pseudo R^2	17.18%	20.78%
Log pseudolikelihood	-427.882	-204.991
N	747	453

Table 3

Robustness checks for table 7 use an alternative measure for VC local experience based on all past investments. The dependent variable of *laterstage* is a dummy variable that equals 1 if portfolio firms received VC investment at seed or early stage and 0 otherwise. Three dimensions of patent activity are adopted as new independent variables. Patent application, granted patent and patent citation take the natural logarithm of the number of portfolio firms' patent applications, granted patents and patent citation respectively before VC investment. Control variables are previously used and definitions are in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(2) Later stage	(4) Later stage	(6) Later stage
Distance	0.008	0.007	0.008*
	(1.57)	(1.39)	(1.70)
Local exp	-0.057***	-0.061***	-0.069***
	(-5.26)	(-5.61)	(-6.50)
Distance*Local exp	-0.005*	-0.003	-0.004
	(-1.74)	(-1.20)	(-1.54)
Co-investors	-0.004	0.000	-0.007
	(-0.16)	(0.01)	(-0.29)
VC equity amount	0.025**	0.030***	0.035***
	(2.33)	(2.83)	(3.29)
CVC	-0.058	-0.075	-0.088*
	(-1.28)	(-1.52)	(-1.69)
GVC	0.081	0.112*	0.118*
	(1.28)	(1.88)	(1.94)
VC age	0.014	0.016	0.025
	(0.72)	(0.83)	(1.28)
VC past success	-0.057	-0.049	-0.065
	(-0.91)	(-0.79)	(-1.08)
Patent application	0.126***		
	(8.63)		
Patent application*	0.000		
Distance	(0.02)		
Granted patent		0.179***	
		(7.42)	
Granted patent*		0.007	
Distance		(0.88)	
Patent citation			0.137***
			(6.42)
Patent citation*			0.010
Distance			(1.17)
Year dummy	YES	YES	YES
country dummy	YES	YES	YES
Pseudo R^2	26.99%	26.78%	26.25%
Log pseudolikelihood	-343.830	-344.806	-347.295
N	774	774	774

Table 4

Robustness checks for table 8 use an alternative measure for VC local experience based on all past investments. Three dimensions of patent activity are adopted as new independent variables. *Follow-on funding* is used as a dependent variable which equals 1 if portfolio firms receive the follow-on funding from the initial lead VC and 0 otherwise. Patent application, granted patent and patent citation take the natural logarithm of the number of portfolio firms' patent applications, granted patents and patent citation respectively before VC investment. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(2) Follow-on funding	(4) Follow-on funding	(6) Follow-on funding
Distance	0.017***	0.018***	0.018***
	(2.93)	(3.08)	(3.00)
Local exp	0.020	0.018	0.019
	(1.48)	(1.41)	(1.43)
Distance*Local exp	-0.002	-0.001	-0.002
	(-0.58)	(-0.39)	(-0.41)
Co-investors	0.117***	0.120***	0.119***
	(3.85)	(3.94)	(3.90)
VC equity amount	0.002	0.004	0.004
	(0.13)	(0.32)	(0.32)
CVC	-0.090	-0.094	-0.093
	(-1.53)	(-1.62)	(-1.61)
GVC	-0.018	-0.016	-0.015
	(-0.28)	(-0.25)	(-0.23)
VC age	-0.016	-0.013	-0.014
	(-0.64)	(-0.52)	(-0.54)
VC past success	0.258***	0.257***	0.258***
	(3.20)	(3.19)	(3.20)
Venture age	-0.033	-0.025	-0.026
	(-1.20)	(-0.89)	(-0.94)
Patent application	0.038*		
	(1.80)		
Patent application* Distance	-0.007 (-0.80)		
Granted patent		-0.038	
		(-1.17)	
Granted patent* Distance		0.006 (0.50)	
Patent citation			-0.015
			(-0.56)
Patent citation* Distance			0.004 (0.45)
Year dummy	YES	YES	YES
Country dummy	YES	YES	YES
Stage dummy	YES	YES	YES
Pseudo R^2	17.49%	17.30%	17.22%
Log pseudolikelihood	-426.268	-427.261	-427.694
N	747	747	747

Table 5

Robustness checks for table 9 use an alternative measure for VC local experience based on all past investments. Three dimensions of patent activity are adopted as new independent variables. The dependent variable is *successful exits* which is a dummy variable equal to 1 if VCs exit the investment via IPO or M&A and 0 otherwise. Patent application, granted patent and patent citation take the natural logarithm of the number of portfolio firms' patent applications, granted patents and patent citation respectively before VC investment. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(2) Successful exits	(4) Successful exits	(6) Successful exits
Distance	0.011	0.011	0.010
	(1.53)	(1.53)	(1.46)
Local exp	-0.002	-0.002	-0.004
	(-0.13)	(-0.11)	(-0.23)
Distance*Local exp	-0.004	-0.004	-0.003
	(-0.79)	(-0.83)	(-0.63)
Co-investors	0.027	0.023	0.026
	(0.77)	(0.68)	(0.76)
VC equity amount	0.043***	0.043***	0.040**
	(2.73)	(2.70)	(2.51)
CVC	-0.080	-0.080	-0.075
	(-1.40)	(-1.42)	(-1.33)
GVC	-0.235*	-0.238*	-0.246*
	(-1.79)	(-1.81)	(-1.82)
VC age	0.002	0.002	-0.000
	(0.06)	(0.08)	(-0.00)
VC past success	0.192**	0.191**	0.203***
	(2.54)	(2.53)	(2.68)
Venture age	-0.000	-0.002	-0.003
	(-0.00)	(-0.05)	(-0.09)
Round number	0.059*	0.057*	0.056*
	(1.90)	(1.85)	(1.83)
Patent application	-0.017		
	(-0.75)		
Patent application* Distance	-0.001 (-0.07)		
Granted patent		-0.009	
		(-0.26)	
Granted patent* Distance		0.001 (0.11)	
Patent citation			0.007
			(0.28)
Patent citation* Distance			-0.014 (-1.57)
Year dummy	YES	YES	YES
Country dummy	YES	YES	YES
Stage dummy	YES	YES	YES
Pseudo R^2	20.89%	20.79%	21.12%
Log pseudolikelihood	-204.716	-204.964	-204.125
N	453	453	453

Table 6

Additional analysis aims to examine the effect of same city experience on VC investment decisions. The dependent variable of *laterstage* is a dummy variable that equals 1 if portfolio firms received VC investment at seed or early stage and 0 otherwise. *Same city exp* is measured by a dummy variable that equals 1 if the lead VC firm invested in the same city as the entrepreneurial company and 0 otherwise. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Later stage	(2) Later stage
Distance	0.008	0.013**
	(1.43)	(2.32)
Same city exp	-0.216***	-0.217***
	(-6.95)	(-7.30)
Distance*Same city exp		-0.017***
		(-2.99)
Co-investors	0.007	0.017
	(0.29)	(0.68)
VC equity amount	0.044***	0.041***
	(3.95)	(3.76)
CVC	-0.039	-0.019
	(-0.79)	(-0.39)
GVC	0.063	0.075
	(0.98)	(1.24)
VC age	-0.012	-0.012
	(-0.63)	(-0.62)
VC past success	-0.118*	-0.101
	(-1.79)	(-1.52)
Year dummy	YES	YES
Country dummy	YES	YES
Pseudo R^2	21.20%	24.13%
Log pseudolikelihood	-371.116	-357.283
N	774	774

Table 7

Additional analysis aims to examine the effect of same city experience on the relationship between geographic distance and VC-portfolio firm partnership performance. The dependent variable in the first column uses *follow-on funding* as a dependent variable which equals 1 if portfolio firms receive the follow-on funding from the initial lead VC and 0 otherwise, while the second column is a dummy variable equal to 1 if VCs exit the investment via IPO or M&A and 0 otherwise. *Same city exp* is measured by a dummy variable that equals 1 if the lead VC firm invested in the same city as the entrepreneurial company and 0 otherwise. The definition of other variables is shown in table 1. Robust standard errors are applied across all regressions. Average marginal effects are reported in the table. ***, **, and * represent 1%, 5%, and 10% significance level respectively.

	(1) Follow-on funding	(2) Successful exits
Distance	0.020***	0.010
	(3.28)	(1.43)
Same city exp	0.053	0.034
	(1.41)	(0.81)
Distance* Same city exp	0.013*	0.019**
	(1.65)	(2.11)
Co-investors	0.122***	0.019
	(3.99)	(0.56)
VC equity amount	0.003	0.042***
	(0.23)	(2.73)
CVC	-0.095	-0.088
	(-1.64)	(-1.50)
GVC	0.005	-0.233*
	(0.08)	(-1.90)
VC age	-0.005	-0.001
	(-0.20)	(-0.05)
VC past success	0.280***	0.172**
	(3.52)	(2.21)
Venture age	-0.026	0.000
	(-0.91)	(0.00)
Round number		0.058*
		(1.89)
Year dummy	YES	YES
Country dummy	YES	YES
Stage dummy	YES	YES
Pseudo R^2	17.31%	21.03%
Log pseudolikelihood	-427.211	-204.351
N	747	453

Chapter 2: The impact of VC firms' diversification strategy on portfolio firms' performance

Abstract

This research empirically investigates the impact of the diversification strategy of venture capital firms (VCs) on the operational performance (sales growth) and financial performance (ROA) of portfolio firms. The analysis compares VCs' expertise and know-how gained from being prior active investors with the coordination costs associated with being concurrent active investors in firms with diverse business activities. The empirical analysis is conducted using a hand-collected panel dataset consisting of 401 VC-funded UK companies observed over the 2009-2019 period. The results show that expertise obtained from VCs' prior diverse experience is positively associated with portfolio firms' performance. In contrast, coordination costs from VCs' concurrent diversification are negatively associated with portfolio firms' performance. For early-stage investments as opposed to later-stage investments, we find that VCs' prior diversification has a stronger association with operational and financial performance, while VCs' concurrent diversification is associated with lower financial performance. Additional analysis reveals an inverted U-shaped relationship between VCs' current diversification and the operational and financial performance of portfolio firms.

Key words: VCs' prior diversification, VCs' current diversification, portfolio firms' performance

1. Introduction

There is a well-known saying: "Do not put all your eggs in one basket." By contrast, Warren Buffett argued that investors should put all their eggs in one basket and watch the basket very carefully. In reality, it is popular for venture capital firms (VCs) to make investments in different industries or countries. These kinds of companies are referred to as "generalist" VCs (high level of diversification). In contrast, some VCs, which are referred to as "specialist" VCs (low level of diversification), specialise in one or several industries. In most cases, instead of offering physical facilities, VCs apply knowledge stocks to interact with portfolio firms (Matusik and Fitza, 2012). The use of different strategies and unique characteristics of VCs (e.g., monitoring role) provide a distinct context to investigate the impacts of portfolio diversification on firm performance.

Previous papers have not distinguished between past and current diversification of VCs. However, it is important to know that these two aspects have different implications: VCs' prior diversification is related to accumulation of diverse experience and knowledge assimilation, while current diversification for each investment year is associated with coordination among investments. This project argues that VCs' prior diversification and current diversification are two different dimensions and related to different factors. Thus, they may have different effects on firm performance.

VCs' prior diversification is a process of accumulation of know-how and expertise. Past diversification strategies enable VCs to develop diversified experience, which in turn helps them make better decisions and affect portfolio firms' performance. For example, diverse experience obtained through prior diversification could assist young ventures in coping with high uncertainties and environmental changes.

Different from prior diversification, current diversification strategy has important implications for VCs in terms of coordination among portfolios in different industries. Coordination costs arise from conducting more due diligence, distributing resources across different projects and managing a variety of portfolios, which create challenges for VCs in terms of monitoring and adding value to their investee firms. When VCs' investments become more diversified, the limited nature of resources such as time and expertise makes the implementation of diversification strategies costly (Knill, 2009).

Furthermore, based on contingency theory, this project also examines whether VCs' diversification strategy is contingent upon the investment stage. Early-stage ventures rely on outside support because of their lack of expertise and capitals. Since engaging in early-stage investment requires VCs to interact more frequently with entrepreneurial companies, we expect that VCs' experience developed through past diversification could be more helpful in coaching young ventures at an early stage than at a later stage.

Early-stage portfolio firms attract more attention from VCs (e.g., evaluation of market conditions and opportunities). VCs may have to allocate more time and resources to the development of early-stage ventures, which also influences their current diversification due to the limited nature of time and financial restrictions. Therefore, early-stage investment could have a moderating effect on the relationship between VCs' current diversification and portfolio firms' performance as well.

The dataset was hand-collected from Thomson One and FAME. Our final sample consists of 401 VC-funded UK firms during the period 2009 to 2019. The main focus of this project is the impacts of VCs' (prior and current) diversification strategy on portfolio firms' performance. The results indicate that VCs' prior diversification related to accumulation of diverse experience positively affects the financial and operational performance of portfolio companies, while VCs' current diversification associated with coordination costs has a negative effect on portfolio firms' performance (ROA and sales growth). We further show that early-stage ventures have a significantly positive moderating effect on the relationship between VCs' prior diversification and portfolio companies' performance.

We also conducted additional analyses to develop our hypotheses by examining a non-linear relationship between VCs' (prior and current) diversification and portfolio firms' performance. We found that entrepreneurial companies benefit from a moderate level of current diversification by VCs (i.e., an inverted U-shaped relationship). However, there is a U-shaped relationship between VCs' prior diversification and portfolio firms' performance, although the results are not significant.

This paper contributes to VC literature by addressing the following research gaps. Firstly, previous papers have focused on the exit performance (e.g., IPO and acquisition versus liquidation), partly because they cannot access financial information about VC-backed companies (Wang and Wang, 2012). Successful VC exits do not mean that VC investment diversification benefits ventures in terms of their financial performance and potential growth. This project focuses on the financial and operational performance of portfolio firms using recent data for the UK. Secondly, previous works do not distinguish between VCs' prior and current diversification. In this paper, we discuss VCs' diversification strategy in more detail by incorporating time-based dimensions of their diversification strategy. Thirdly, this study further explores the role of VCs' diversification in the context of early-stage investment. Fourthly, the project also extends the study by Matusik and Fitza (2012), who found a negative relationship between past diversification and VCs' exit performance. However, we argue that while past diversification experience has negative effects on VCs' performance, it may benefit portfolio firms' performance. Finally, to our best knowledge, this paper is the first to examine a curvilinear relationship between VCs' diversification strategy and portfolio firms' performance.

2. Literature review

2.1. VCs' prior diversification and accumulation of diverse experience

Empirically, researchers have explored the relationship between VCs' portfolio diversification and firm performance. They found that more diversified VC investments generally lead to lower VC performance (Matusik and Fitza, 2012; Bellavitis et al., 2014; Yang et al., 2014). However, empirical works do not recognise the difference between VCs' current-year diversification and prior diversification, and the importance of past diversification receives considerably less attention. Unlike VCs' current diversification, which is related to coordination among portfolios, prior diversification is associated with expertise accumulation. The more diversified the investment VCs have made previously, the more likely they are to possess broader knowledge. Thus, VCs' past diversification represents the extent of their experience and knowledge diversity.

The implementation of previous diversification strategies enables VC investors to gain experience and know-how from various business activities, such as selection, valuation and nurturing of entrepreneurial firms. It equips VCs with flexibility and adaptability (Matusik and Fitza, 2012). For instance, if high uncertainties appear in one industry, venture capitalists can realise the risks and pay attention to other industries. Matusik and Fitza (2012) asserted that knowledge stocks with a similar nature can be more efficiently leveraged. A lower level of prior diversification might enable VCs to obtain deeper knowledge and expertise due to efficient processing of similar information (Yang et al., 2014). The accumulation of diverse experience enables VCs to deal with environmental changes and turbulence, boost effective interaction with portfolio companies, and make better decisions. Therefore, it is valuable to the development of entrepreneurial firms.

However, VCs' diversified experience derived from past diversification could also lead to lower portfolio firm performance in some circumstances. For example, the experience interaction between the board and the VC firm could cause agency problems when the goals and interests of directors are not aligned with those of the VC investor. Moreover, the board of directors aims to protect the interests of the majority of shareholders, and VC investors may have different objectives compared to other shareholders, like founders. In this case, agency problems could be intensified by the interaction and thus undermine firm performance. Information asymmetries between VCs and portfolio firms are another factor that can weaken the positive effect of VCs' prior diversification.

Zarutskie (2010) found that management teams with more prior VC investing experience and more experience of managing entrepreneurial firms present higher exit performance. However, he further indicated that VC management teams have lower performance when they have more general human capital measured by managers' education in the fields of business, law, science and engineering. Additionally, task-specific and industry-specific experience of VCs obtained through prior work experience can better predict VCs' performance compared to general human capital gained by education.

Previous diversification provides an opportunity to examine VCs' absorptive capacity, which involves the acquisition and assimilation of knowledge (Yang et al., 2014). Prior diversification strategies should have long-term benefits for VCs, since diversification develops the process of experience accumulation in various fields so that VCs better respond to potential market uncertainties.The monitoring and resource provision roles allow VCs to take advantage of their human capital developed through prior diversification to achieve better outcomes. Furthermore, diversified experience could enhance portfolio firms' performance by offering useful suggestions. VCs with diverse experience in different industries may help entrepreneurial companies earn larger market shares, as their innovative products could be applied in multiple industries.

Compared to diversified investments, previous investment specialisation may equip VC investors with deeper knowledge, as well as broader and more mature intra-industry networks (Bellavitis et al., 2014). With deep knowledge gained through previous specialisation, VC investors might perceive uncertainty as an opportunity in that field. However, the impact of the level of prior diversification depends on a degree of relatedness. For instance, if an entrepreneurial company designs a new nanomaterial, VCs that specialise in the biotechnology industry could realise that the new nanotechnology can be applied in the development of biotechnological products. Therefore, VCs that previously conducted a specialisation strategy in relation to the biotechnology industry are helpful in coaching their portfolio firms. However, what if the VC firm was dedicated to other industries, like computer hardware, or the application of new technology becomes more complicated? In this scenario, specialised VCs fail to make use of their industry-specific experience, but diverse experience could better help VCs address challenges through the combination of different knowledge dimensions. For example, VC investors that have gained expertise in the chemical, pharmaceutical, medical and biotechnology industries are more advantageous to the application of a new nanomaterial.

VCs are different from other institutional investors (e.g., mutual funds and banks) because of their need to create value. They primarily rely on intangible assets like human capital rather than physical assets facilitating knowledge-sharing and experience exchange with their portfolio counterparts (Yang et al., 2014). Since young ventures mainly rely on outside resources to help them grow and address uncertainty, diversity of experience as a valuable human capital could develop and promote the interaction between VC investors and entrepreneurial companies in order to improve decision-making processes. The transfer of expertise and knowledge plays a crucial role in value-added services by VCs because entrepreneurial firms do not share operations with them. It is expected that experience in managing diversified investments might also benefit VCs by enabling them to better monitor and interact with financed firms. Therefore, VCs' diverse experience developed through past diversification could improve firm performance by enabling VCs to proactively coach their investee companies.

H (1): VCs' prior diversification related to diverse experience accumulation positively affects portfolio firms' performance.

2.2. VCs' current diversification and coordination among portfolios

VCs may apply an investment approach colloquially referred to as a "spray and pray" strategy, which aims to invest a little funding and provide limited governance to a larger number of start-up companies, to diversify their portfolio firms (Ewens et al., 2018). Ewens et al. (2018) provided evidence that over the last decade, the VC investment model has fundamentally evolved. This evidence raised a question about whether the evolution of the VC investment model (e.g., current diversification strategy) has either positive or negative effects on portfolio firms' performance.

Current diversification strategy requires VCs to coordinate their investments in terms of allocation of resources and the extent of their involvement in portfolio companies. Thus, it would also potentially influence portfolio firms' performance in addition to the implications for VCs, like risk mitigation. A higher level of current diversification results in greater coordination costs, which reduces the efficiency of monitoring and restricts support for portfolio companies. For example, diversifying investments in different industries forces VCs to conduct complex analyses to determine which industry is more promising and take time to make decisions about allocating resources. In contrast, a lower level of diversification minimises coordination costs, because VCs can simply focus more on an entrepreneurial firm with better performance by using peer group analyses without considering uncertainties arising from other industries. Less consideration helps VCs save time and effort, allowing them to coordinate their portfolios and improve the process of decision-making.

Continuous investments in transaction-relevant industries produce superior firm-level resources and capabilities which will lower ultimate transaction costs (i.e., contractual hazards) (Hopp and Lukas, 2014). Information asymmetries and uncertainty induce VCs to invest in some particular industries or firms (Norton and Tenenbaum, 1993). Based on the evidence from VCs in the US, Gompers et al. (2008) found that a higher level of industry specialisation leads to more successful exits. When there is a lower level of knowledge spillovers, "specialist" VCs are less likely to participate in early-stage investments compared to "generalist" VCs (Kang et al., 2011).

Yang et al. (2014) argued that if VCs manage portfolio companies that are highly uncorrelated, a diversification strategy will adversely affect the VCs' ability to absorb knowledge, because VC absorptive capacity works when the knowledge is related to what VCs already know. They explained that absorptive capacity is dynamic and VCs need to constantly reshape it in order to prepare themselves for entering new territories. Consequently, in this paper, it is expected that VC firms manage their currently diversified portfolios with the use of expertise generated from prior diversification.

VCs adopt diversification strategies in order to mitigate risks, generate synergies and increase success rates. The implementation of investment diversification is often regarded as a trade-off between risks and returns based on corporate finance theory. Through strategic diversification, VCs are able to obtain unique resources, competitive advantage, broader horizons and valuable experience that is difficult to imitate (Cressy et al., 2014). However, diversification decisions are affected by environmental uncertainties (Norton and Tenenbaum, 1993). In addition, investing in industries unrelated to VCs' know-how will result in extra costs, and VCs tend to do business in areas in which they are already well-informed. Accordingly, portfolio diversification does not make economic sense for VCs (Norton and Tenenbaum, 1993).

Kang et al. (2011) combined VC diversification with real option frameworks and noted that VCs' diversification decisions and post-investment effort are analogous to call options. Diversification offers options to VCs to liquidate poor-performing portfolios and focus more on other projects. However, when VC investors diversify into industries that they do not possess relevant knowledge and experience in, the greater industry diversification negatively affects fund performance (Buchner et al., 2017). VC managers rationally make investment decisions in terms of diversification. From a risk-based perspective, portfolio-level risks impact the screening process and due diligence (Buchner et al., 2017).

Firms with a preference for exploiting and exploring a range of areas are accompanied by diversified resources and are less likely to be subjected to intense competitive pressures due to a variety of choices from diversification (Barnett et al., 1994). Diversification strategies allow VCs to combine outside information so that they are sensitive to environmental changes such as technological changes and policy updates. Moreover, social capital like networks can be discovered and developed by investment diversification. For example, diversification decisions motivate VCs to make investments in industries or countries they are not familiar with. In this case, VCs tend to form a syndicate with other VC partners to reduce risks and uncertainty. This procedure boosts collaboration and coordination between VCs, builds trust, and creates the opportunity for the next cooperation. The possible experience-sharing also benefits both sides when different types of VCs coach their portfolio together.

Although empirical literature has discussed how VC portfolio diversification affects VC performance, papers about VC diversification are still limited, especially when it comes to the dimension of portfolio firms' performance. Cressy et al. (2014) used traditional financial theory (investment diversification increases performance) and resource-based theory (investment specialisation increases performance) to explain that industry diversification is associated with lower VC fund performance. They found that diversification by country, on the other hand, has a positive influence on VC exit performance. Their results suggest that it is more challenging for VCs to invest in different industries than in different nations.

Diversified companies need to take into account the suitability of their diversification strategy, as costs can arise from inefficient allocation of resources (Campa and Kedia, 2002). Buchner et al. (2017) found that a higher level of diversification is positively associated with VC fund performance. They further researched the persistence of VCs' diversification strategies and illustrated that previous industry (stage) diversification will positively affect current industry (stage) diversification.

Although diversification strategies satisfy VCs' goals, this could be at the expense of better involvement in their portfolio firms. Specifically, a diversification strategy requires VCs to carry out more due diligence and prepare enough capital, which is usually a large amount. When VCs' current investment becomes more diversified, the monitoring time and resource distribution for each portfolio firm will be less and less due to the limited nature of time and possessed resources. Buchner et al. (2017) documented that when venture capitalists make investments in more companies in different industries, they will spend less time and devote less attention to each portfolio. Consequently, VCs' current diversification is not positively associated with portfolio firms' performance.

H (2): VCs' current diversification related to coordination among portfolios negatively affects portfolio firms' performance.

2.3. The moderating effect of VCs' investment stage

The impacts of VCs' prior and current diversification on portfolio firms' performance could be contingent upon the VCs' investment stage, which is related to uncertainty. Early-stage investments, which are likely to generate uncertain consequences (e.g., failure), are considered to be riskier for VCs than later-stage transactions (Chaplinsky and Gupta-Mukherjee, 2016). Gupta and Sapienza (1992) documented that demand, technological, resource and management uncertainties put early-stage ventures at a higher risk than their later-stage counterparts.

On the one hand, the value of VCs' prior diversification related to accumulation of diverse experience could increase in early-stage investments. Early-stage entrepreneurial firms need more monitoring activities and support from VC investors (Croce et al., 2019). VCs are able to leverage their diversified experience to effectively recognise and evaluate opportunities, identify potential risks, and help their investee firms quickly react to technological innovativeness. Hence, higher uncertainties in the early investment stage render VCs' prior diversification more valuable. Matusik and Fitza (2012) found that VC diversification is more valuable to VC performance in the context of early-stage ventures.

Additionally, since start-ups lack the experience and knowledge required for dealing with an uncertain environment that threatens their survival and growth, external resources (e.g., VC human capital) play a crucial role in promoting portfolio firms' further development. Compared to later-stage ventures, early-stage firms require greater assistance from VCs because of greater business risks. Due to the characteristics of higher risks in early-stage investments, VCs tend to more actively provide industry and market knowledge to entrepreneurial companies, which enhances the internal efficiency and external market position of early-stage ventures (Gupta and Sapienza, 1992).

On the other hand, the influence of VCs' prior diversification on portfolio firms' performance may decrease in the context of early-stage ventures. VCs are not familiar with portfolio companies when they initially invest. Agency problems are likely to be created in the case of early-stage investing if the interests and goals of the entrepreneurial firm's management team are not aligned with those of the VC firm. As a result, VCs fail to provide effective value-added services to portfolio companies. Compared to diverse expertise, specialised knowledge associated with a venture's business may be more helpful in dealing with risks and uncertainties (Cressy et al., 2014).

In the later stage, information asymmetries between VCs and portfolio firms are reduced with the increase in familiarity. VC-backed companies will become more transparent if they prepare to go public. The value of prior diversification could decrease in the later stage, as ventures have fewer requirements for monitoring and coaching.

H (3): VCs' investment stage has a moderating effect on the relationship between VCs' prior diversification and portfolio firms' performance.

VCs' investment stage also has implications for the implementation of their current diversification strategy, because early-stage deals increase VC firms' monitoring costs. Early-stage firms need aggregate availability of funding to achieve technological innovation and economic growth (Chaplinsky and Gupta-Mukherjee, 2016). Consequently, VCs have to pay particular attention to early-stage companies, and their current diversification strategy could be constrained by them. Namely, VCs have to make a trade-off between their attention to investee companies and the extent of diversification.

Gupta and Sapienza (1992) found that VCs prefer less industry diversity if they are specialised in early-stage ventures. Norton and Tenenbaum (1993) documented that VCs' preference for diversification is contingent on the presence of uncertainty in the external environment. According to a survey-based analysis of 98 US companies, they argued that VCs specialise in industries they are familiar with if their portfolio involves early-stage firms. In other words, early-stage ventures characterised by a higher level of uncertainty induce VCs to concentrate on given industries.

Early-stage ventures could benefit from outside networks introduced by VCs' current diversification. The establishment of connection and cooperation with other entrepreneurial companies in the early stage may help VC-funded firms gain complementary resources and achieve rapid growth. In addition, higher risks in early-stage investments are likely to result in poor performance, which implies a loss of reputation for VCs (Buzzacchi et al., 2015). Therefore, the pressure to pursue reputation enables VCs to dedicate more time and resources to early-stage ventures by adjusting their current diversification strategy, which potentially improves portfolio firms' performance. Carter and Van Auken (1994) concluded that VCs that invest in early-stage ventures are more willing to spend more time and exercise control over their financed firms.

In contrast with early-stage companies, later-stage ventures save VCs time and effort in terms of monitoring and guidance. Consequently, VCs' flexibility might be improved by either implementing new due diligence or paying attention to other portfolio firms. A switch of focus to other investments may affect VCs' current diversification strategy related to due diligence and resource allocation, and result in a negative impact on later-stage firms.

H (4): VCs' investment stage has a moderating effect on the relationship between VCs' current diversification and portfolio firms' performance.

3. Data sources and sample

Data about VC investments and their characteristics were hand-collected from Thomson One. Our dataset includes only first-time VC investments for portfolio companies located in the UK. The UK has the largest and most mature VC industry in Europe, accounting for approximately 40% of total annual private equity deals (Cressy et al., 2014). Compared to VC investments in the US, the UK VC market receives much less attention from empirical papers (Bellavitis et al., 2014). The first-time VC investment means that it is the first time for portfolio firms to receive the VC funding.

We first used Thomson One to identify VC investments that took place during the period 2008 to 2019[3], resulting in 2,320 VC-funded companies. Then we manually matched information on financial performance and characteristics of boards of directors obtained from FAME. Matching manually was necessary, as some companies had changed their name, and matching Thomson One and FAME data

[3] Company information on FAME covers this period.

involved the following criteria: 1) website link; 2) postcode; 3) business description; 4) founding date should be earlier than incorporation date; 5) same city and industry. Our matched sample [4] includes 478 VC-funded companies with available financial and board-of-directors information. Our sample shrunk because of the missing financial information (e.g. ROA) in FAME. Specifically, after obtaining 2,320 portfolio firms from Thomson One, we checked how many VC-backed firms have information listed in FAME, because young ventures do not usually disclose financial information. Surprisingly, 700 firms could be found by searching FAME. Then we identified whether the 700 firms were exactly the same as those in Thomson One based on the criteria and whether they had the required data. As a result, our sample consists of 478 VC-funded firms.

Firms with only a single-year observation were excluded, as we needed at least two observations for each company to calculate sales growth. We also excluded companies that went public prior to or after VC investment, due to the following reasons: 1) our interest and focus is only on VC-backed companies that remain private throughout their development. VC-backed companies that go public after receiving VC investment might have different characteristics or performance metrics compared to those that remain private all the time. They may have different motivations, growth trajectories, and exit strategies, which could affect their performance and make them less comparable to other VC-backed companies in the sample; 2) including VC-backed companies that went public after receiving VC investment could introduce bias into the sample. These companies may have received additional financing or resources that other private VC-backed companies did not have access to, which could affect their growth and performance; 3) we want to focus on the performance of VC-backed companies before exit, rather than after exit. We can avoid doing the analysis on the performance both before and after the IPO, which may complicate the analysis and obscure the effect of VC investment on pre-exit performance. Although we could delete the years after IPO, there are a lot of works to do before IPO such as conducting due diligence, ensuring compliance with regulations, and hiring an investment bank, and VCs will also be dedicated to it impairing VC monitoring role. These things need to be done before IPO affecting firm performance and the effect of VC on portfolio firms. 4) We can focus on a more homogeneous group of companies that received VC investment and remained private throughout their development. This would increase the validity and accuracy of the analysis and help us do a more straightforward analysis on the effect of VC monitoring role.

Corporate VC investments were excluded as well because they have different goals and structures, such as longer investment durations compared to other VCs (Milosevic, 2018). The final sample consists of 401 portfolio firms with 2,034 observations during the period 2009 to 2019.[5]

[4] Matched sample means that the companies from Thomson One are exactly the same as those in FAME and their data is merged from the two databases.
[5] 2008 is excluded as only seven observations were available.

Some financing rounds may involve more than one VC firm (VC syndication) to reduce risks. In this case, lead VC firms, which are likely to have more motivations and incentives to assist portfolios in achieving better performance because they have provided a larger financial injection, were selected. According to the empirical papers (Milosevic, 2018), there are three empirical ways to define lead VC investors: 1) VC investors who acquire the largest equity amount in the first financing round; 2) VC investors who take the largest stake based on cumulative financing rounds; and 3) VC investors who take part in the maximum number of financing rounds. When more than one VC firm satisfied the criteria, we chose the closest one, as the lower transaction costs of monitoring allow the closest VC investor to exert more repercussions on portfolio firms' performance (Kolympiris et al., 2018). Consequently, consistent with empirical evidence, the lead VC was rigorously applied and selected in syndicated investments so that we were more likely to capture the interaction effects between VCs and the invested firms. Since we introduced the following financing rounds, the lead VC firm could change over subsequent rounds and variables would be time-variant.

To facilitate the classification of businesses into industry sectors, various coding systems have been developed. Two such systems are the Standard Industrial Classification (SIC) and the Venture Economics Industry Classification (VEIC) codes. They provide a consistent and standardized way to identify and compare businesses within the same industry sector. The Venture Economics Industry Classification (VEIC) codes are a proprietary coding system developed by Venture Economics, a data and research firm specializing in private equity and venture capital data. These codes are specifically designed to classify companies within the private equity and venture capital industry. Both systems provide numerical codes that represent the industry sector to which a company belongs. While SIC codes are used for general economic classification across various industries, VEIC codes focus specifically on companies within the private equity and venture capital ecosystem. Consistent with empirical papers (Dai et al., 2012; Wang and Wang, 2012; Meuleman et al., 2017), according to the Venture Economics Industry Classification (VEIC), VC-funded companies are classified based on the following industries: communication and media, biotechnology, medical/health/life science, semiconductors/other electronics, computer related, and non-high technology. Table 1 shows the specific industry distribution of VC investee firms. It indicates that VCs have a preference for high-tech industries (73.56%). More specifically, computer-related and communication and media industries are the two most popular, which together take up 51%. This is consistent with Dai et al. (2012). Overall, the industry distribution of entrepreneurial firms in our sample is representative.

4. Variables

4.1. Dependent variables

The financial performance of VC-funded companies is measured by return on assets

(ROA). Operational performance is measured as annual sales growth of portfolio firms. The time horizon of performance measures is one year.

4.2. Independent variables

Industry experiences involve know-how in exploring and sifting through promising investment opportunities in the pre-investment period, and an ability to lead entrepreneurial firms towards a successful exit through the provision of value-added services in the post-investment stage (Zhang and Pezeshkan, 2016; Gompers et al., 2010). Hopp and Lukas (2014) pointed out that the ability to provide high-quality suggestions and screen business proposals can be improved by industry experience. Heterogeneous experience helps portfolio firms cope with environmental changes, come up with creative solutions and take advantage of a wide range of information and resources (Ganotakis and Love, 2012). Accordingly, this paper focuses on the role of VC diversification by industry.

Consistent with the traditional measurement of diversification (Cressy et al., 2014; Yang et al., 2014), *VC prior div* by industry is calculated by the Herfindahl–Hirschman Index (HHI)= $1 - \sum_{k=1}^{n} \mathrm{p}_{\mathrm{k}}^{2}$. The calculations of HHI are based on the investments that a VC firm had made in the past 10 years before the portfolio company was financed by the VC, where *p* is the proportion of investments in the *k*th industry category based on the three-digit VEIC[6], and *n* indicates the total number of industry categories. For example, suppose a VC firm invests in a portfolio firm in 2010, VC prior div is measured based on the VC investments between 2000 and 2009. *VC current div* by industry for each year is measured in an analogous manner based on the HHI. The variables are time-variant and calculated according to the investment information from Thomson One. Additionally, sensitivity analyses are conducted by adopting the two-digit VEIC level in order to assess the different levels of relatedness. The results are very similar.

4.3. Control variables

For board characteristics of portfolio firms, the control variable of board size is included. Empirical evidence suggests that board size is negatively correlated with profitability (Mak and Kusnadi, 2005). A larger board size is accompanied by increased coordination mechanism costs, which could result in low efficiency. However, young ventures with fewer board members may lack resources and managerial supports that a larger board could offer to entrepreneurial companies (Gloor et al., 2020). VC firms often have larger board sizes compared to traditional corporate boards due to their specific role as shareholders and investors in the companies they fund. The larger board size is a reflection of the VC firm's active involvement in the strategic direction and decision-making of their portfolio

[6] The three-digit VEIC classifies industries according to 17 categories.

companies. As active shareholders, VCs seek to have a strong presence on the company's board of directors to ensure their interests are represented and to actively contribute to the company's growth and success. VC firms often appoint executive directors and non-executive directors who possess specific expertise and experience relevant to the company's industry and growth stage. Having a larger board with diverse skills and networks can provide valuable insights and connections that can benefit the portfolio company.

Empirical economics papers find either a positive or a negative relationship between the presence of females on the board and firm performance (Shehata et al., 2017). From a psychological perspective, female reasoning is different from that of males. The variable of *Female* is measured as the number of females on the board to control for the effect of gender. We also use the variable of average age of directors as a proxy for directors' general experience. We admit that the average age of directors is not an accurate proxy for experience in the context of corporate governance and leadership. While age can be associated with accumulated experience in certain cases, it does not always correlate directly with the depth or relevance of experience that is essential for effective directorship.

International VCs refer to the practice of venture capital firms investing in start-ups and early-stage companies located in countries outside of their home country. It involves cross-border investments where VC firms from one country invest capital in promising companies located in other countries, often with the aim of supporting their growth and expansion. International VCs are defined as if their headquarters are located outside the home country of portfolio firms even if they have local offices. Empirical papers show that international VCs are more experienced and familiar with foreign markets than domestic VCs (Tykvová, 2018). Cross-border VC investments supply start-ups with multiple exit choices, foreign capital supports and international networks (Zhang and Pezeshkan, 2016; Wang, 2017). However, international VCs may encounter "liabilities of foreignness", which increase monitoring costs and uncertainties for their investments (Buchner et al., 2018). Cumming et al. (2016) expected international investors to be unable to provide huge assistance to entrepreneurs due to geographic barriers across countries. They showed that cultural distance negatively influences successful exits by VCs (IPO and acquisition). Therefore, we used an indicator variable to control for the effect of foreign VCs.

VCs often co-invest in a project to deal with uncertainties and risks arising from start-ups. The profitability of entrepreneurial firms could be improved by VC syndication because of heterogeneous skills, a wide range of inputs and collaboration (Tian, 2012). Prior studies have shown that syndicate-backed companies are more innovative and have better operating performance compared to individual ones (Tian, 2012; Guo and Jiang, 2013). Hence, a binary indicator was applied which took the value of 1 if the investment involved two or more VC investors, and 0 otherwise.

Other VC characteristics controlled for included the cumulative financing round number. To test the moderating effect of the investment stage, we created a dummy variable which was equal to 1 if it was a seed or early VC investment, and 0 otherwise. Year fixed effects were also included. Table 2 displays the specific definitions of variables.

5. Model specification

Hausman tests suggest that the fixed-effects (FE) model is preferable to the random-effects (RE) model. An FE estimator is advantageous to control omitted variable bias because of unobserved heterogeneity if it is time-invariant (Wooldridge, 2010). In order to control the problems of potential heteroskedasticity and autocorrelation, the robust standard errors were clustered at the portfolio firm level.

Firstly, to examine hypotheses 1 and 2, we conducted regressions to estimate the following model by using the whole sample:

$$\begin{aligned}\textit{Portfolio firms' performance} = {} & a_0 + a_1\, \textit{VC prior div} + a_2\, \textit{VC current div} \\ & + \textit{Control variables} + e\end{aligned}$$

Then we introduced the interaction terms to examine hypotheses 3 and 4. The regressions were based on the following model:

$$\begin{aligned}\textit{Portfolio firms' performance} = {} & a_0 + a_1\, \textit{VC prior div} + a_2\, \textit{VC current div} \\ & + a_3\, \textit{VC prior div * Early stage} \\ & + a_4\, \textit{VC current div * Early stage} \\ & + \textit{Control variables} + e\end{aligned}$$

where *Portfolio firms' performance* refers to sales growth and ROA of portfolio companies. Control variables include firm size, directors' age, firm age, shareholders, females, board size, foreign market presence, cumulative round, international VC, stage and year fixed effects. Specific definitions of variables are shown in table 2. $a_1(+)$, $a_2(-)$, $a_3(+/-)$ and $a_4(+/-)$are used to verify hypotheses 1, 2, 3 and 4 respectively.Expected signs are in parentheses.

6. Summary statistics

Table 3 lists the summary statistics of the sample, including means, maximum, minimum and standard deviation. On average, the values of the variables of sales growth and ROA for VC-funded companies are 0.25 and -0.23 respectively. The mean value of VCs' prior diversification is about 0.63, indicating that VCs tend to make diversified investments and accumulate diversified industry experience over time. However, VCs manage less diversified portfolios (0.38) in each investment year. The level of VCs' current diversification is less than that of previous diversification on average partly because VCs carefully and prudently implement their diversification strategy each year. Chaplinsky and Gupta-Mukherjee (2016) documented that performance assessments are continually updated by VCs, and portfolio companies with poor performance are less likely to attract subsequent financing. The average age of VC-financed firms is less than 10 years (9.6).

Table 4 provides the correlation matrix among variables. The correlation coefficients between all variables are lower than 0.3 except for the correlation between VCs' prior diversification and same industry experience (0.31). In contrast with Matusik and Fitza (2012), who found that VCs' previous diversification by industry has a negative effect on their performance, the correlation matrix shows a positive impact of past diversification (VCs' diverse experience) on portfolio firms' performance in terms of ROA and sales growth. It is worth noting that VCs' past diversification is positively associated with current diversification. We could speculate that VC investors followed their previous pattern of portfolio diversification, and that the larger the number of diversified investments they had made in the past, the greater the possibility that they would conduct more due diligence and invest in portfolios in different industries.

If potential inertia and path-dependency exist in their diversification strategy, VCs' prior diversification is likely to be highly correlated with current diversification. However, the correlation coefficient between VCs' prior and current diversification is only 0.13, which indicates that the two measures capture different dimensions of VC diversification. One possible reason is that although VCs managed diversified investments in the past, they carefully make decisions about diversifying their current-year investments. Furthermore, VCs' diversification strategy depends on the external environment (Norton and Tenenbaum, 1993; Matusik and Fitza, 2012), like global financial and economic conditions. If VC investors perceive that a specific industry has a huge potential growth opportunity in the (near) future, they could focus more on that industry. Instead, when there is a high uncertainty, VCs will avoid the investment in that industry.

Additionally, some VCs that are newly established start their businesses with a narrow focus and expand their portfolio diversification over time (Matusik and Fitza, 2012). However, the correlation coefficient does verify the standpoint to some extent that past and current diversifications are two different dimensions or associated with different factors. It is true that when VCs believe that they have invested in enough portfolios or encountered financial constraints, those VCs will not necessarily conduct more due diligence that may diversify portfolio investments, even if the level of their previous diversification is high. The values of VIF of all variables are not higher than the traditional threshold of 10, suggesting that the regression analysis is less likely to suffer from multicollinearity.

7. Empirical results

In table 5, models 1 to 3 are performed by the dependent variable of sales growth, whereas models 4 to 6 are regressed on ROA. To make comparisons, model 1 and model 4 contain only control variables. The majority of control variables are significant and have expected signs. The cumulative financing round number significantly and negatively affects the ROA of portfolio companies. One possible reason for this is that more VCs might be participating in the investment into the portfolio firms, leading to potential agency problems, which increase investment costs and lower management efficiency (Meyer and Shao, 1995).Similarly, board size is also negatively correlated with the financial performance of VC-funded companies. In addition, portfolio companies in the early stage tend to have lower performance.

The regression results also show that international VC firms are able to enhance sales and ROA of their invested counterparts even though the results for the latter are not statistically significant. VCs contribute to sales growth if they previously invested in the same industry as portfolio firms. Firm size is positively and significantly associated with sales growth and ROA, whereas firm age has a negative relationship with sales growth and ROA. The results are consistent with Guo and Jiang (2013). Interestingly, we find that females have a significantly positive influence on entrepreneurial firms' sales growth. Recent academic journals have emphasised the role of females in corporate governance. They have generally examined the positive relationship between females and firm performance (Isidro and Sobral, 2015).

Models 2 and 5 in table 5 add the main variables of VCs' prior and current diversification. The results suggest a significant and positive relationship between VCs' prior diversification and portfolio firms' performance in terms of sales growth and ROA (model 2: a=0.520, $P<0.05$; model 5: a=0.580, $P<0.01$). The coefficients of VCs' prior diversification are significant and in line with hypothesis 1. However, VCs' current diversification negatively impacts on both sales growth and ROA of portfolio firms (model 2: a=-0.257, $P<0.01$; model 7: a=-0.356, $P<0.01$). Results for VCs' current diversification are also significant and consistent across all regressions. Hence, hypothesis 2 is verified.

In table 5, models 3 and 6 are full models and contain the interaction terms which aim to examine hypotheses 3 and 4. Early-stage investment has a positive moderating effect on the relationship between VCs' prior diversification and sales growth (model 3: a=0.581, $P<0.1$). Namely, the value of VCs' prior diversification on sales increases when their portfolio firms are in the early stage. Similarly, the result for model 10 indicates that early-stage investment positively moderates the effect of VCs' prior diversification on portfolio firms' financial performance (ROA) (a=0.460, $P<0.01$). The regression results also show that VCs' prior diversification tends to have a larger positive effect on operational performance (sales growth) of entrepreneurial firms than their financial performance (ROA) in the early stage. This makes sense, since VCs' previous diversification by industry could help them to gain knowledge of the sales of innovative products and accumulate market-related expertise. Consequently, VCs can more efficiently leverage their diverse experience to promote sales in the early stage.

In terms of the interaction terms between VCs' current diversification and early-stage investment, the result of model 3 suggests that early-stage investment has a positive moderating effect on the relationship between VCs' current diversification and portfolio firms' operational performance, but the results are not significant. However, in model 6, we find that there is a significant and negative moderating impact of early-stage investment on the relationship between VCs' current diversification and ROA ($a=-0.227$, $P<0.5$).

The results of the moderating effects of VCs' investment stage are also in line with Carter and Van Auken (1994), who concluded that VCs take a more active managerial role in entrepreneurial companies in the early stage compared to those in the later stage.

8. Quadratic relationship between VCs' diversification and portfolio firms' performance

Portfolio diversification is identified to have a curvilinear relationship with firm performance. Matusik and Fitza (2012) demonstrated a U-shaped function between VCs' diversification and fund performance: a lower level of diversification advances VC performance because coordination costs are low, indicating that knowledge stocks with a similar nature can be more efficiently leveraged, while a higher level of diversification enables VCs to receive broad information which facilitates their problem-solving ability. Similarly, Yang et al. (2014) focused on corporate venture capital (CVC) activities and showed that the industry diversification of CVC is related to firm value creation in a U-shaped relationship. By contrast, Palich et al. (2000) conducted a meta-analysis on the diversification–performance relationship and suggested that a moderate level of diversification yields better performance (inverted U-shape). The inconsistent results based on traditional analysis also indicate the variation in diversification strategies.

To our best knowledge, no paper examines a quadratic relationship between VCs' diversification and portfolio firms' performance. Table 6 presents the results on the curvilinear relationship between VCs' diversification strategy and portfolio firms' performance. The coefficients of control variables still remain very similar to those in table 5. Model 1 indicates that VCs' prior diversification associated with diversified experience accumulation has a U-shaped relationship with both sales growth and ROA of portfolio firms. Namely, VC-financed companies benefit more (achieve better performance) from lower or higher levels of prior diversification by VCs. However, the results are not significant.

From the perspective of knowledge stocks of VCs' prior diversification, a lower level of past diversification is likely to equip VCs with deeper know-how, which benefits portfolio firms if their business is related to VCs' past diversification, whereas a high level of previous diversification enables VCs to possess broader knowledge that is useful in dealing with uncertainties.

By contrast, we find that VCs' current diversification is significantly correlated with the operational and financial performance of portfolio firms in an inverted U-shaped function. Specifically, portfolio companies achieve better performance as VCs' current diversification increases, and then their performance starts to become lower when arriving at a certain point. One interpretation of this result is that portfolio firms could benefit from network expansion with an increase in VCs' current diversification level. However, after reaching a certain level of current diversification, it is possible for the performance of an entrepreneurial company to be undermined because supports from VCs (e.g., time and capitals) are restricted.

Figures 1 and 2 plot the curvilinear relationship between sales growth and ROA, respectively, and VCs' current diversification based on the following measured equations:

$$\text{Sales growth}=-1.155*\text{Current\_div}^2+0.545*\text{Current\_div}-1.651 \qquad (1)$$

$$\text{ROA}=-0.681*\text{Current\_div}^2+0.115*\text{Current\_div}-6.250 \qquad (2)$$

It is noticeable that the turning points of VCs' current diversification are lower than the average value, indicating that VCs tend to overdiversify their investments. Although diversification strategy is an important means for VCs to diversify risk and improve VC performance, our results suggest that there is also a trade-off between VCs' current diversification (VCs' performance) and portfolio firms' performance. Since VCs have a responsibility to offer value-adding services, they have to take into account the extent to which they should diversify their investments so that they can ensure better performance of portfolio firms, especially when they conduct a "spray and pray" strategy.

9. Endogeneity

If a VC firm already has a bundle of well-performing portfolio firms, it does not need to diversify risk and so a lower level of current diversification is required (reverse causality). To address the potential endogenous problem between VCs' current diversification and portfolio firms' performance, two-stage least-squares (2SLS) regressions were undertaken by using VC firm age as an instrumental variable, which is consistent with Buchner et al. (2017). They argued that portfolio composition can be better selected by more experienced VC firms compared to less experienced ones, as VC firms with high general experience enjoy better access to high-quality deal flow (relevance criterion). In addition, exclusion restriction is inherently not testable. However, VC prior diversification related to VC diverse experience accumulation in our model captures VC expertise to some extent as well. Moreover, we re-estimate the empirical models by adding VC age. The results show that the coefficients are very low (around 0.01) and highly insignificant (P-value is larger than 0.6). Accordingly, we do not expect that VC age associated with VC general experience has a direct effect on portfolio firms' performance, and thus the instrument satisfies the exclusion criterion. We admit that there is a limitation to use VC age as IV since old VCs may provide better value-adding services to portfolio firms. We still use VC age as IV as there is no better IV available and Buchner et al. (2017) has used VC age as IV for diversification,

We used the same control variables from models 2 and 5 in table 5. Table 7 presents the results of IV analyses. In columns 1 and 3, the dependent variables are VCs' current diversification (first-stage regressions). VC firm age has a significantly negative effect on VCs' current diversification (Sales growth model: a=-0.113, P<0.01; ROA model: a=-0.097, P<0.01). F-statistics are larger than 10 at the first-stage regressions. To the rule of thumb, the IV is valid. The second-stage regressions suggest that the negative relationship between VCs' current diversification and portfolio firms' performance remains unchanged, except that the effect of VCs' current diversification becomes less significant in the sales growth model (Sales growth model: a=-0.358, P<0.1; ROA model: a=-0.368, P<0.01).

10. Robustness check

We took the following steps to test whether the main results are robust or not. First, the variables of VCs' prior and current diversification were recalculated based on a two-digit VEIC level in order to test the different levels of relatedness. We re-ran the regressions based on our full models. The results remained very similar (see table A1 in the appendix).

Second, we excluded the VCs that were just established when they invested in portfolio firms or had not diversified their investment in the past, because these VCs with low activity may not be representative in general. This is a common approach and practice in VC empirical literature (Sorensen, 2008; Fitza et al., 2009; Matusik and Fitza, 2012). The results did not change, except that the interaction term between VCs' current diversification and early-stage investment became insignificant (see table A2 in the appendix).

11. Conclusions

This paper mainly examined the relationship between VCs' diversification strategy and portfolio firms' performance based on the analysis of hand-collected panel data. VCs' prior and current diversifications are related to different factors. Accordingly, we argue that they have different effects on portfolio firms' performance. Most importantly, the decision-making relating to diversification strategy cannot be merely regarded as a channel to reduce risks. Instead, it is proposed that VCs' diversification provides opportunities for VCs to accumulate diverse knowledge and experience, which are valuable human capital and benefit VCs' future investments (i.e., portfolio firms' performance).

This study has several implications for VC diversification literature. Empirical studies rarely examine the influence of VCs on portfolio companies, especially in the field of VC diversification strategy. We discussed the time-based dimensions of VCs' diversification: VCs' prior and current diversification. Specifically, VCs' prior diversification is related to experience accumulation, reflecting the extent of VCs' expertise diversity, whereas VCs' current diversification is associated with coordination among portfolios. Furthermore, this project finds that VCs' prior diversification has a positive influence on portfolio firms' performance in terms of ROA and sales growth, while there is a negative relationship between VCs' current diversification and firm performance. Compared to the level of VCs' prior portfolio diversification, VCs prudently implement their current diversification strategies.

Based on contingency theory, we anticipated that the effect of VCs' diversification strategy on portfolio firms' performance is also contingent on the context of VCs' investment stage. The results suggest that VCs' diverse experience derived from prior diversification is more valuable to sales growth and ROA of portfolio firms in the early stage.

This study further explored whether a non-linear relationship exists between VCs' diversification and portfolio firms' performance. We found that VCs' current diversification has a significantly inverted U-shaped relationship with financial and operational performance of entrepreneurial companies. However, VCs' prior diversification is associated with portfolio firms' performance in a U-shaped function, although the results are insignificant.

This paper contributes to the literature on VC human capital. For instance, unlike previous papers which have focused on the role of VC task-specific human capital (Milosevic, 2018), this paper explored the importance of industry-wide experience resulting from VCs' prior diversification strategy. Industry experience diversity can be regarded as an invaluable human capital for VCs and one that improves portfolio companies' performance. A positive relationship between prior diversification and portfolio firms' performance (ROA and sales growth) also verified the empirical conclusion that VCs with more experience enable entrepreneurial firms to achieve better-quality financial reports (accounting information) (Agrawal and Cooper, 2010).

In terms of the implications for VC management, it is important to realise that VCs' diversification strategy is not only beneficial to risk mitigation, which is identified by empirical studies (Buchner et al., 2017), but also a process of accumulating diversified expertise, which could benefit the future development of young ventures. For example, diverse knowledge and experience obtained through past diversification could be helpful in coping with environmental changes and uncertainties. Moreover, VCs should prudently select and diversify portfolio firms by strategically allocating resources to different projects. Our results indicate that VC managers tend to overdiversify their investments, and there is a trade-off between VCs' current diversification and portfolio firms' performance. Because they have a responsibility to offer value-adding services, VC managers have to decide the extent to which they should diversify their deals in order to achieve better performance of portfolio firms. This implication may be particularly useful to young VC firms because they are in pursuit of reputation derived from higher portfolio firms' performance.

There are implications for companies seeking VC financing. It is evident that VC firms with a history of high diversification can bring a wealth of expertise and experience to the table. However, it is equally important to seek out VC investors who are currently managing a narrower portfolio. These VCs might be better positioned to provide more focused attention, resources, and strategic guidance to portfolio companies. Future research could further examine the investment patterns of VCs. Namely, during a specific period, whether VCs may make asset allocation to specific industries depending on their time horizon and current market conditions, and their diversified experience is gradually accumulated in the long run.

There are some limitations in this research, which can be considered and addressed in future works. First, this paper pays attention to the UK VC market. Future analysis should concentrate on evidence from other countries or markets to examine the generalisability of our results. Second, this project only examines the relationship between portfolio firms' performance and VCs' diversification. Future research needs to explore what determinants affect VCs' management when making diversification decisions. For example, in order to have a deeper understanding of the decisions of VCs' diversification, analysts can discuss whether and how VCs adjust their investments when they encounter financial constraints or markets become volatile (e.g., Covid-19 in 2020). Third, we exclusively consider the importance of VCs' diversification strategy by industry. However, VCs may also try to diversify their portfolios by other channels, such as country or investment stage. Future works should refine this paper through the exploration of these channels. Fourth, the reliance on ROA and sales growth as performance measures can indeed become problematic, especially when the filing requirements for financial data in the UK differ based on firm size. The discrepancy in filing requirements may introduce biases in the sample used for performance analysis, potentially leading to inaccurate or incomplete conclusions. Finally, the measurement of diversification could be biased. Classifying a company's business activities into distinct sectors or industries can be subjective and prone to ambiguity. Different classification systems or criteria can yield different results, impacting the assessment of diversification.

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Figures

Figure 1

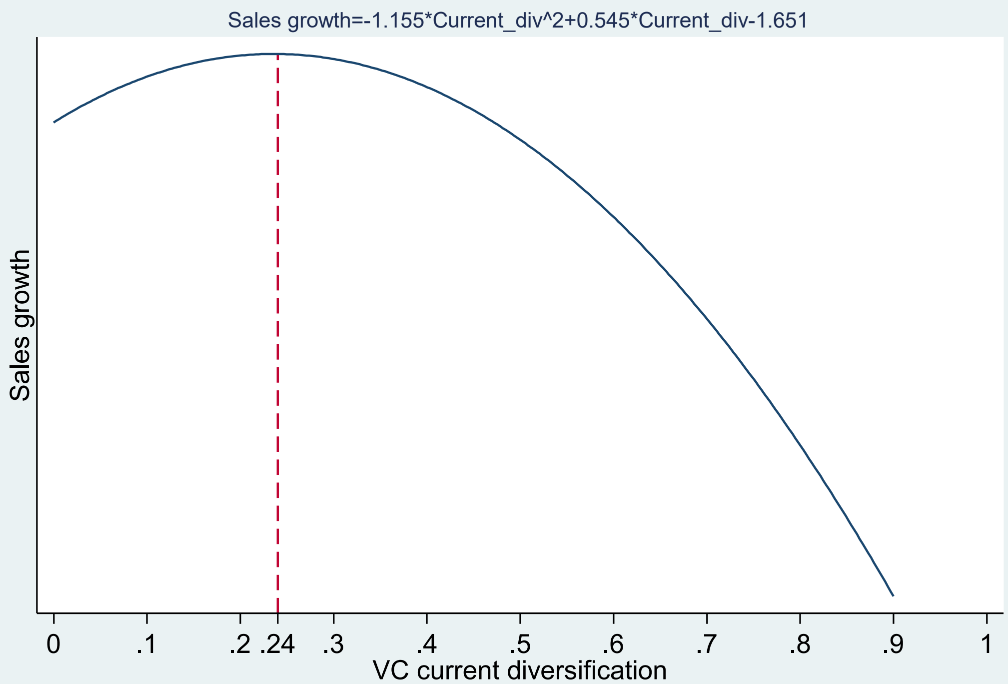

Figure 1. Curvilinear relationship between sales growth and VC current diversification

Figure 2

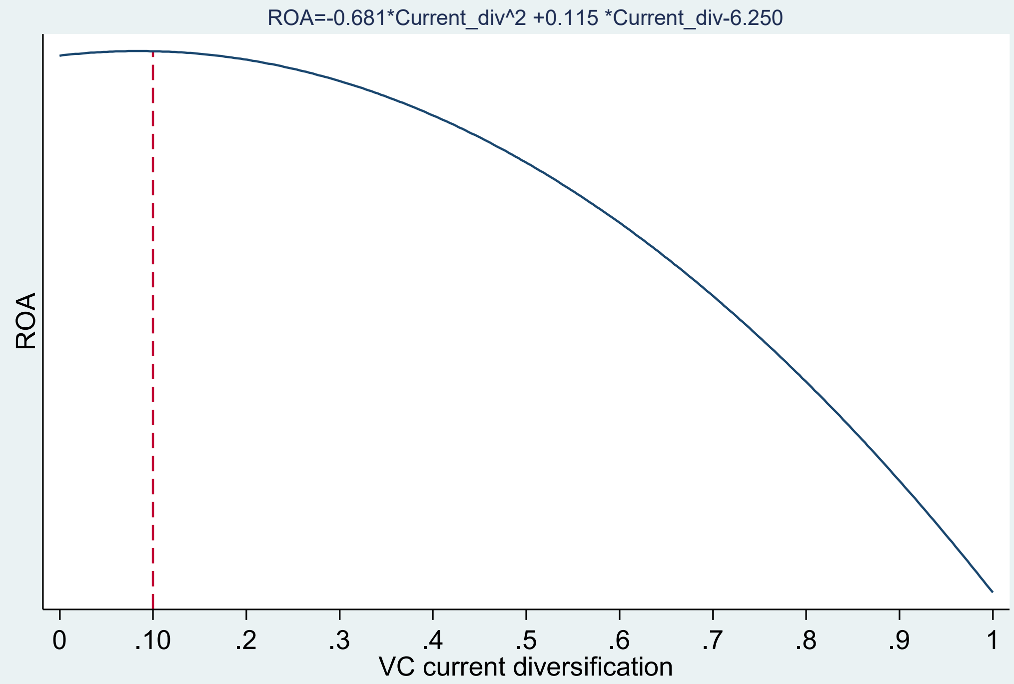

Figure 2. Curvilinear relationship between ROA and VC current diversification

Table 1: The industry distribution of entrepreneurial firms

Industry	Frequency	Percent	Cum.
Communication and media	92	22.94%	22.94%
Biotechnology	37	9.23%	32.17%
Medical/health/life science	41	10.22%	42.39%
Semiconductors/other electronics	11	2.74%	45.13%
Computer related	114	28.43%	73.56%
Non-high technology	106	26.44%	100%
Total	401	100%	100%

Table 2: Definitions of variables

Variables:	Definitions
Dependent variables	
Sales growth	Entrepreneurial firms' annual sales growth.
ROA	Financial performance measured as return on assets.
Independent variables	
Firm size	Measured by the natural logarithm of the total assets of VC-funded company.
Director's age	Natural logarithm of the average age of directors.
Firm age	Natural logarithm of VC portfolio firms' age which is the difference between portfolio firms' incorporation date and VC investment date.
Female	Natural logarithm of one plus the total number of females on the board.
Board size	Natural logarithm of the total members on the board.
Cumulative round	Natural logarithm of the cumulative financing round number by VCs.
International VC	A binary indicator which takes the value of 1 if the investment involves at least one foreign VC and 0 otherwise.
Same industry experience	A binary indicator which takes the value of 1 if VC previously invested in the same industry as portfolio firms and 0 otherwise.
VC syndication	A binary indicator which equals 1 if the investment involves two or more VC investors and 0 otherwise.
Early stage	A dummy variable which equals 1 if VC invests in seed or early stage and 0 otherwise.
VC prior div	Calculated by HHI based on the investments that a VC firm made in the past ten years before the portfolio company is financed by the VC.
VC current div	Calculated by HHI based on the investments that a VC firm made in each fiscal year of invested firms.

Table 3: Summary statistics

The table includes raw variables which do not take a logarithm. The loss of observations of sales growth is because of the calculations and missing data. The definitions of variables are shown in Table 2.

	N	Mean	St.Dev	min	max
Sales growth	1457	.251	.725	-.895	4.83
ROA	2034	-.225	.563	-2.984	4.578
Firm size (￡mil)	2034	11.178	11.239	.031	77.275
Director's age	2034	48.843	6.373	26.5	73
Firm age	2034	9.571	7.001	1	37
Female	2034	.380	.678	0	6
Board size	2034	4.382	1.898	1	12
Cumulative round	2034	1.855	1.359	1	12
International VC	2034	.434	.496	0	1
Same industry experience	2034	.568	.495	0	1
VC syndication	2034	.599	.490	0	1
Early stage	2034	.282	.450	0	1
VC prior div	2034	.629	.235	0	.904
VC current div	2034	.379	.298	0	.859

Table 4: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Sales growth	1.00													
(2) ROA	0.14*	1.00												
(3) Firm size	0.11*	0.25*	1.00											
(4) Director's age	-0.06	0.12*	-0.03	1.00										
(5) Firm age	-0.06	0.15*	0.02	0.22*	1.00									
(6) Female	0.03	0.02	0.07	0.08	0.01	1.00								
(7) Board size	0.04	-0.11*	0.02	0.17*	-0.03	0.23*	1.00							
(8) Cumulative round	0.03	-0.27*	0.11*	-0.09*	-0.09*	0.01	0.10*	1.00						
(9) International VC	0.06	-0.10*	0.08	-0.08	-0.01	0.04	0.06	0.25*	1.00					
(10) Same industry experience	0.20*	0.09*	0.06	-0.01	-0.06	0.03	0.01	0.05	0.04	1.00				
(11) VC syndication	0.16*	0.11*	0.06	-0.01	0.03	-0.15*	0.04	0.11*	0.14*	-0.02	1.00			
(12) Early stage	-0.07	-0.26*	-0.18*	-0.04	-0.24*	0.03	0.05	0.03	0.09*	-0.01	-0.06	1.00		
(13) VC prior div	0.13*	0.15*	0.08	-0.04	0.03	0.03	0.04	0.02	-0.01	0.31*	0.04	-0.05	1.00	
(14) VC current div	0.01	-0.11*	-0.03	-0.02	-0.02	-0.07	0.05	0.03	-0.05	-0.03	0.01	0.02	0.13*	1.00

* shows significance at the 0.01 level

Table 5

This table shows the relationship between VC diversification strategy and portfolio firms' performance. Estimated coefficients and t-statistics (in parentheses) based on fixed effects mode are reported. Heteroskedasticity-robust standard errors are clustered at portfolio firm level. The definitions of variables are shown in Table 2.* p<0.1, ** p<0.05, *** p<0.01.

	(1) Sales growth	(2) Sales growth	(3) Sales growth	(4) ROA	(5) ROA	(6) ROA
Firm size	0.136**	0.124**	0.114**	0.267***	0.249***	0.242***
	(2.53)	(2.34)	(2.23)	(7.60)	(7.63)	(7.50)
Director's age	0.053	0.047	0.046	0.628*	0.587*	0.579*
	(0.19)	(0.16)	(0.16)	(1.79)	(1.70)	(1.70)
Firm age	-0.418**	-0.418**	-0.416**	-0.123**	-0.110**	-0.107**
	(-2.59)	(-2.60)	(-2.59)	(-2.22)	(-2.23)	(-2.21)
Female	0.311***	0.287***	0.282***	0.052	0.035	0.035
	(2.88)	(2.71)	(2.64)	(1.10)	(0.73)	(0.75)
Board size	0.071	0.065	0.063	-0.126***	-0.142***	-0.140***
	(1.00)	(0.93)	(0.90)	(-2.68)	(-3.23)	(-3.22)
Cumulative round	-0.054	-0.044	-0.040	-0.166***	-0.145**	-0.148**
	(-0.38)	(-0.31)	(-0.28)	(-2.62)	(-2.54)	(-2.55)
International VC	0.344***	0.340***	0.332***	0.088	0.083	0.083
	(4.17)	(4.14)	(3.90)	(1.57)	(1.61)	(1.63)
Same industry experience	0.408***	0.283***	0.278***	0.175***	0.032	0.023
	(5.42)	(3.24)	(3.16)	(4.21)	(0.68)	(0.47)
VC syndication	0.059	0.024	0.037	0.131**	0.085	0.093
	(0.61)	(0.23)	(0.35)	(2.02)	(1.47)	(1.63)
Early stage	-0.131	-0.148	-0.469**	-0.120**	-0.118***	-0.321***
	(-1.19)	(-1.35)	(-1.99)	(-2.57)	(-2.84)	(-3.11)
VC prior div		0.520**	0.367*		0.580***	0.436***
		(2.60)	(1.88)		(5.53)	(4.50)
VC current div		-0.257***	-0.232**		-0.356***	-0.294***
		(-2.85)	(-2.32)		(-6.19)	(-5.10)
VC prior div*			0.581*			0.460***
Early stage			(1.92)			(3.01)
VC current div*			-0.151			-0.227**
Early stage			(-0.78)			(-2.05)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.662	-1.569	-1.329	-6.529***	-6.191***	-5.993***
	(-1.28)	(-1.22)	(-1.03)	(-4.70)	(-4.56)	(-4.40)
N	1457	1457	1457	2034	2034	2034
adj. R-sq	0.113	0.130	0.135	0.158	0.222	0.232

Table 6

This table shows the nonlinear relationship between VC diversification strategy and portfolio firms' performance. Estimated coefficients and t-statistics (in parentheses) based on fixed effects mode are reported. Heteroskedasticity-robust standard errors are clustered at portfolio firm level. The definitions of variables are shown in Table 2.* p<0.1, ** p<0.05, *** p<0.01.

	(1) Sales growth	(2) ROA
Firm size	0.131**	0.251***
	(2.54)	(7.80)
Directors age	0.073	0.607*
	(0.26)	(1.80)
Firm age	-0.435**	-0.119**
	(-2.66)	(-2.43)
Female	0.297***	0.035
	(2.91)	(0.75)
Board size	0.069	-0.141***
	(0.99)	(-3.28)
Cumulative round	-0.060	-0.156**
	(-0.42)	(-2.77)
International VC	0.331***	0.085*
	(3.85)	(1.67)
Same industry experience	0.280***	0.027
	(3.20)	(0.59)
VC syndication	-0.006	0.073
	(-0.05)	(1.32)
Early stage	-0.163	-0.122***
	(-1.49)	(-3.01)
VC prior div	-0.010	0.274
	(-0.02)	(1.03)
VC current div	0.545**	0.115
	(-2.03)	(0.68)
$(\text{VC prior div})^2$	0.520	0.300
	(1.74)	(1.04)
$(\text{VC current div})^2$	-1.155***	-0.681***
	(-3.03)	(-3.16)
Year fixed effects	Yes	Yes
Constant	-1.651	-6.250***
	(-1.28)	(-4.70)
N	1457	2034
adj. R-sq	0.139	0.229

Table 7

This table displays the regression results of endogeneity (IV analysis). T-statistics or z-values are reported in parentheses. VC age is an instrumental variable which takes the natural logarithm of lead VC firms' age. The definitions of variables are shown in Table 2.* p<0.1, ** p<0.05, *** p<0.01.

	(1) VC current div	(2) Sales growth	(3) VC current div	(4) ROA
Firm size	0.000	0.053***	-0.008	0.127***
	(0.01)	(3.21)	(-1.17)	(9.70)
Director's age	-0.029	-0.144	0.044	0.460***
	(-0.48)	(-0.94)	(0.92)	(5.06)
Firm age	0.000	-0.135***	-0.013	0.052***
	(0.04)	(-3.85)	(-1.48)	(3.41)
Female	-0.039*	0.073	-0.040**	0.048*
	(-1.88)	(1.47)	(-2.29)	(1.68)
Board size	-0.021	0.048	-0.029**	-0.136***
	(-1.32)	(1.37)	(-2.20)	(-5.65)
Cumulative round	0.030**	-0.024	0.028**	-0.233***
	(2.26)	(-0.70)	(2.40)	(-9.89)
International VC	-0.012	0.025	-0.008	-0.063**
	(-0.76)	(0.60)	(-0.57)	(-2.57)
Same industry experience	-0.033**	0.220***	-0.039***	0.048**
	(-2.06)	(5.79)	(-2.89)	(2.10)
VC syndication	-0.017	0.241***	-0.018	0.132***
	(-1.06)	(6.47)	(-1.32)	(5.78)
Early stage	0.008	-0.130***	0.008	-0.217***
	(0.45)	(-2.67)	(0.58)	(-7.62)
VC prior div	0.312***	0.330***	0.298***	0.354***
	(9.09)	(3.71)	(10.29)	(5.98)
VC age	-0.113***		-0.097***	
	(-12.30)		(-12.49)	
VC current div		-0.358*		-0.468***
		(-1.68)		(-3.19)
Year fixed effects	Yes	Yes	Yes	Yes
Constant	0.688**	-0.144	0.449**	-3.823***
	(2.57)	(-0.20)	(2.12)	(-9.25)
N	1457	1457	2034	2034
F-statistics	12.92***		13.13***	
Prob. >Chi sq.		0.000		0.000
R-sq	0.131	0.082	0.105	0.250

Appendix

Table A1

Robustness checks by recalculating the variables of VC prior and current diversification based on a two-digit VEIC level. The table reports estimated coefficients and t-statistics (in parentheses) based on fixed effects model. Heteroskedasticity-robust standard errors are clustered at portfolio firm level. The definitions of variables are shown in Table 2.* p<0.1, ** p<0.05, *** p<0.01.

	(1) Sales growth	(2) ROA
Firm size	0.113**	0.240***
	(2.20)	(7.36)
Director's age	0.030	0.569*
	(0.11)	(1.67)
Firm age	-0.415**	-0.109**
	(-2.56)	(-2.22)
Female	0.279***	0.032
	(2.62)	(0.68)
Board size	0.067	-0.138***
	(0.95)	(-3.19)
Cumulative round	-0.031	-0.141**
	(-0.21)	(-2.44)
International VC	0.334***	0.082
	(3.88)	(1.65)
Same industry experience	0.297***	0.034
	(3.37)	(0.73)
VC syndication	0.030	0.090
	(0.29)	(1.59)
Early stage	-0.418*	-0.309***
	(-1.80)	(-2.90)
VC prior div	0.385*	0.446***
	(1.71)	(4.46)
VC current div	-0.258**	-0.308***
	(-2.49)	(-5.12)
VC prior div	0.524*	0.457***
*Early stage	(1.74)	(2.81)
VC current div	-0.155	-0.232**
*Early stage	(-0.78)	(-2.01)
Year fixed effects	Yes	Yes
Constant	-1.259	-5.926***
	(-0.99)	(-4.34)
N	1457	2034
adj. R-sq	0.134	0.233

Table A2

Robustness checks by excludingVC firms with low activity. The table reports estimated coefficients and t-statistics (in parentheses) based on fixed effects model. Heteroskedasticity-robust standard errors are clustered at portfolio firm level. The definitions of variables are shown in Table 2.* p<0.1, ** p<0.05, *** p<0.01.

	(1) Sales growth	(2) ROA
Firm size	0.119**	0.233***
	(2.39)	(7.12)
Director's age	0.037	0.721**
	(0.13)	(2.07)
Firm age	-0.442**	-0.107**
	(-2.58)	(-2.21)
Female	0.274**	0.040
	(2.58)	(0.83)
Board size	0.071	-0.113***
	(0.96)	(-3.12)
Cumulative round	-0.050	-0.161***
	(-0.33)	(-2.72)
International VC	0.310***	0.086*
	(3.94)	(1.72)
Same industry experience	0.303***	0.022
	(3.18)	(0.44)
VC syndication	0.010	0.115**
	(0.09)	(2.07)
Early stage	-0.799**	-0.489***
	(-2.30)	(-3.23)
VC prior div	0.591*	0.485***
	(1.81)	(3.74)
VC current div	-0.214**	-0.307***
	(-2.02)	(-5.20)
VC prior div	0.927**	0.643***
*Early stage	(2.12)	(2.98)
VC current div	-0.098	-0.149
*Early stage	(-0.48)	(-1.33)
Year fixed effects	Yes	Yes
Constant	-1.449	-6.498***
	(-1.12)	(-4.68)
N	1386	1927
adj. R-sq	0.146	0.226

Declaration

Versions of Chapter 2 titled “Do VCs punish portfolio firm directors for underperformance?”, co-authored with Kevin Amess and Simona Mateut, have been presented at various conferences.

Chapter 3: Do VCs punish portfolio firm directors for underperformance?

Abstract

Venture Capital (VC) monitoring is said to improve the corporate governance of portfolio firms. We examine whether this impacts director accountability by empirically testing whether director turnover is more sensitive to firm performance in firms with VC backing compared to firms without VC backing. Based on a sample of UK companies observed over the 2009-2019 period we find there is higher director turnover in VC portfolio firms with lower performance and growth. The findings are robust to alternative performance measures and estimation methods. The results are consistent with VCs improving director accountability for portfolio firm performance.

Keywords: VC-backed firms; director turnover; portfolio firm performance

1. Introduction

Prior research shows that Venture Capitalists (VCs) play a role in the composition and changes of portfolio firms' executive teams (Heger and Tykvova, 2009). We extend the literature by empirically testing whether executive turnover is more sensitive to firm performance in VC-backed firms compared to non-VC-backed firms. We argue there is a stronger relationship between executive turnover and firm performance in VC-backed firms because VCs are active investors with financial incentives to improve executive accountability.

VCs provide funds to firms in return for an equity stake. It is well-established that VCs are not simply providers of finance. VCs are active investors: monitoring senior management, mentoring and providing portfolio firm managers with guidance on finance and strategy, and providing business contacts (Fried and Hisrich, 1995). The post-investment interaction between VCs and their portfolio firms is often facilitated by their representation on the board of directors (Rosenstein et al., 1993).

From an agency theory perspective, the board of directors is an important governance device that monitors and disciplines senior management, helping align senior managers' and owners' interests (Fama and Jensen, 1983). The characteristics and effectiveness of the board of directors as a governance device have received considerable attention. A key concern in the case of listed companies is that board members are not financially motivated to hold senior management accountable for firm underperformance. This is because board members receive regular payments for serving on the board and make little or no financial investment in the firm (Hart, 1995). In contrast, VCs are motivated to be active investors: their ability to raise future funds and a proportion of their pay are linked to fund performance (Barber and Yasuda, 2017; Metrick and Yasuda, 2010), which is driven by the underlying performance of investee firms. VCs are therefore motivated to be active board members. Consequently, VCs are likely to hold accountable inside board members of firms not achieving performance or strategic goals.

Our empirical analysis is conducted on a unique hand-collected dataset of first-time VC investments in 261 portfolio companies located in the UK. Our VC portfolio firms operate in non-financial industries and are observed over the 2009-2019 period. We construct a control sample of 1241 firms using a manual matching procedure inspired by Cumming et al. (2020) and Guo and Jiang (2013). Specifically, from the population of companies available in FAME, each control company is matched to a VC-backed firm on characteristics observed the year before they receive VC investment using the following five criteria: two-digit SIC industry, postal region, performance, size, and age. In doing so, we build a comprehensive dataset of VC-backed and non-VC-backed firms that are similar before receipt of the first VC investment. Despite being one of the largest and most mature markets in Europe, there is relatively little research on the UK VC market. This may be attributable to the difficulty in obtaining data.

Our evidence shows that VC portfolio companies witness higher director turnover than firms without VC backing. In addition, director turnover in VC portfolio companies is more sensitive to firm performance than in non-VC-funded companies. Looking deeper into the director turnover–firm performance relationship, VC-backed firms experience higher director turnover when their relative performance is in the bottom quartile within their industry. Finally, heterogeneity across VC investment types and the stage at which funding occurs have a differential impact on director turnover in portfolio firms.

Our analysis of the relationship between director turnover and firm growth, both sales and employment growth, shows that it is more sensitive in VC-backed firms. Interestingly, relative sales and employment growth have a different relationship with director turnover. Director turnover is significantly higher in VC-backed firms in the bottom three quartiles of sales growth compared to the highest quartile. In contrast, VC-backed firms in the bottom three quartiles of employment growth do not have significantly different director turnover compared to non-VC-backed firms. These findings are important because there is an implicit assumption in the literature that VCs pursue a growth strategy in their portfolio firms (Standaert et al., 2022). Our evidence suggests that it is sales growth that matters to VCs, not employment growth.

Our results are robust to a series of sensitivity tests. We conduct our analysis on a sample obtained based on an alternative matching procedure. The choice of estimator does not affect our results either: both the fractional response model and a limited dependent variable approach produce qualitatively similar findings. In addition, the results are economically significant. For instance, the likelihood of observing changes in VC-sponsored firms increases relative to non-VC-sponsored peers by 8.4 percentage points as firm performance deteriorates.

Our empirical analysis extends the literature in two ways. First, we add to the strand of research which examines whether VCs are associated with the turnover of the board of directors. Most prior works have focussed on turnover of the initial executive team and firm founders. Heger and Tykvova (2009) show that the presence of VCs promotes the first change of initial executive team in a sample of German high-tech entrepreneurial firms. Similarly, Baker and Gompers (2003) show that within a sample of VC-backed US firms at IPO (Initial Public Offering), there is decreasing likelihood of the firm having a founder CEO when a VC firm has a stronger reputation. The role of VCs in determining portfolio firm governance is further confirmed by Bonini et al. (2012), who report that VCs are associated with CEO replacement. Second, we provide the first evidence linking board turnover with VC-backing and portfolio firm performance. By doing so, we determine that VCs hold board members accountable for firm performance and strategic growth objectives.

The remainder of the paper proceeds as follows. Section 2 reviews the literature and develops the testable hypotheses. Section 3 describes our empirical models and variable construction. Section 4 introduces the data set and provides summary statistics. Section 5 presents the regression results. We present robustness tests and additional analysis exploiting heterogeneity in our sample in Section 6. Section 7 draws the conclusions.

2. Literature review and hypotheses development

2.1 VC monitoring and director turnover

Jensen and Meckling (1976) show that when an owner-manager sells equity to an outside investor, agency costs increase because the owner-manager no longer bears the full costs of pursuing objectives inconsistent with profit-maximisation. In large firms, outside investors usually own most equity while managers own a minority stake, increasing potential agency costs. The board of directors is a corporate governance device whose function, *inter alia*, is to monitor senior managers and attenuate agency costs. The agency relationship between outside VC investors and senior managers in entrepreneurial ventures is different from that in large firms because senior managers often have a large, and sometimes controlling, equity stake.

The nature of the agency relationship between VC investors and senior management in VC-backed firms is not one of opportunism arising from a lack of financial incentive from being a residual claimant (Bruton et al., 2000). First, an agency problem can arise because senior management lack talent (Walsh and Seward, 1990). VC-backed firms are more likely to observe a churning of senior management because the VC identifies which members of the existing team lack the required talent and identify new talent to bring on the board. Second, VCs and board members with significant equity are not in a hierarchical principal-agent relationship. Therefore, the agency problem that arises is one of moral hazard in teams (Holmstrom, 1982). Finally, there might be a lack of agreement on the direction the firm takes (Walsh and Seward, 1990). While VC due diligence should mitigate potential disagreements over the strategies the venture pursues, post-investment, senior managers might still pursue different objectives to those preferred by VCs.

VC board representation, which facilitates monitoring of senior management, is a channel to align interests of senior management and VCs. VCs contractual relations with senior managers permit them to terminate their employment (Sahlman, 1990). Therefore, VCs have the power to hold senior managers in portfolio firms accountable for underperformance. Portfolio firms' board is inclined to be less mature compared to public firms and board members may even pursue their own interests. In this case, the monitoring function is particularly critical for young ventures because they are not subject to market discipline (Garg, 2013). Owing to concentrated ownership and smaller boards, private companies have a stronger monitoring motivation (Gao et al., 2017). Consequently, VCs are potentially motivated to establish a board that is better aligned with their interests.

Heger and Tykvova (2009) argue their evidence of VC instigated executive turnover is consistent with VCs seeking to install more able senior managers. Based on the sample of German entrepreneurial companies, they find that VC investors positively affect the likelihood and speed of turnover of the founding executive team revealing an active function of VCs in the management of investee firms. These findings are consistent with the resource dependence theory of the board of directors, which emphasises the resources each board member provides: expertise, know-how, and a network of contacts. From a resource dependency perspective, VC companies introduce new board members that provide complementary resources to the firm and remove current members if they lack the required resources.

Following the above discussion, we introduce the first hypothesis:

H1: director turnover is higher in VC backed firms than in firms without VC backing.

2.2 Do VCs change the board when portfolio firms underperform?

Research examining the association between board structure and performance largely focuses on listed firms. Indeed, evidence demonstrates that poor firm performance increases the likelihood of CEO turnover in listed companies (Brickley, 2003; Gregory-Smith et al.,2009). Surprisingly, given claims that VCs are active investors that improve corporate governance in investee firms (Chemmanur et al., 2021), there is no empirical analysis of this issue in relation to VC-backed firms. Prior research examines the relationship between VC investment and board turnover (e.g., Heger and Tykvova, 2009), but fails to explore whether VCs become more proactive in changing top management when portfolio firms are underperforming.

VC-backed firms represent an interesting contrast compared to listed firms. The boards of listed firms are said to have little motivation to press for CEO dismissal when confronted by senior executives with incentives to entrench themselves (Gregory-Smith et al., 2009). This scenario contrasts sharply with VC investors whose ownership stake provides them with strong financial incentives to remove underperforming directors. Unlike listed firms, however, VCs are confronted with directors that often have a significant ownership stake in the firm, making their removal difficult (Bruton et al., 2000). Nevertheless, VCs often have board of director representation, which means are well-placed to replace CEOs when they are dissatisfied with firm performance (Rosenstein et al., 1993).

The agency relationship between investor and CEO conforms to the classic agency relationship that underpins the corporate governance problem: the CEO is optimizing a different objective function from shareholders. It is assumed that shareholders want to maximize firm value whereas a senior manager's objective function could include power, status prestige, firm size, consuming perquisites (Hart, 1995). The separation of ownership from control creates an environment where managers can behave opportunistically in pursuit of private objectives that destroy firm value (Fama and Jensen, 1983). Managers' increased equity ownership more closely aligns the managers' interests with equity holders. VCs are well aware of this and ensure senior management in entrepreneurial firms hold a significant equity stake (Fried and Hisrich, 1995). The financial incentives from equity ownership should make managerial opportunism associated with the separation of ownership and control less problematic (Bruton et al., 2000; Garg, 2013).

Since top management's equity ownership provides them with high-powered incentives, underperformance in portfolio firms might not arise from top management behaving opportunistically. We provide two alternative explanations. First, underperformance could arise because top management is of low ability (Walsh and Seward, 1990). It is well-known that VCs due diligence of investee firms includes an appraisal of the top management's team ability (Gompers et al., 2020). Schefczyk and Gerpott (2001) report a correlation between the top management qualifications and firm performance; however, VCs fail to understand this relationship. Nevertheless, management quality is a difficult characteristic to observe and due diligence will not eliminate the adverse selection problem confronting VC investors. Post-investment underperformance provides a signal of top management quality. To an outsider it is difficult to determine whether firm underperformance is due to bad luck or low managerial ability. In contrast, VCs board representation facilitates top management monitoring and are well-placed to determine whether management quality is a factor. If VCs decide that low CEO ability is a factor in determining firm underperformance, we expect to observe CEO turnover.

Second, underperformance could arise because top management pursued a misguided strategy (Walsh and Seward, 1990). Sapienza and Gupta (1994) suggest that there can be good faith disagreements between VCs and top management because there is uncertainty as to which strategy maximizes firm value. VCs and management can disagree over which strategy to pursue. This is an important issue for VCs who seek to be actively involved in strategy formulation (Fried et al., 1998). Given both parties have a significant financial stake in the firm, the disagreement is in good faith. If top management put in effort to pursue a strategy that results in firm underperformance, VC equity ownership and board representation provides them with the financial incentive and means to hold top management accountable (Garg, 2013). Therefore, if VCs decide that top management should be accountable for pursuing a strategy that resulted in firm underperformance, we expect to observe CEO turnover.

The above discussion demonstrates that a VC will hold the CEO of an entrepreneurial venture accountable for firm underperformance if the VC ascribes the underperformance to low CEO ability or the CEO pursuing a strategy over which the VC and CEO disagree. VCs equity investment and board representation therefore provide VCs with the financial incentive and means to change the CEO when an investee firm exhibits underperformance. Theory predicts an empirical relationship between firm underperformance and CEO turnover and so we posit the following hypotheses:

H2: director turnover in VC-backed firms is more sensitive to firm performance than in non-VC-backed firms.

H3: director turnover in VC-backed firms is more sensitive to firm underperformance than in non-VC-backed firms.

2.3 Do VCs change the board when portfolio firms do not achieve growth?

The previous section assumes that goal congruence between the VC and CEO involves maximizing firm performance. However, there is an implicit assumption in some of the VC literature that firms backed by VCs pursue a growth strategy (Standaert et al., 2022). The human capital of a portfolio firm's senior management and access to venture capital, relaxing financial constraints, are potential drivers of firm growth (Colombo and Grilli, 2010). It might also be the case that VCs target for investment firms that have growth objectives (Cosh et al., 2009). Based on similar theoretical arguments as employed in the previous section, we envisage two alternatives. First, the top management of investee firms might fail to achieve VCs growth aspirations for the portfolio firm because top management lack ability (Walsh and Seward, 1990). If the VC hold the CEO accountable for the failure to achieve growth, CEO turnover is likely. Second, there might be good faith disagreement between the top management and the VC over which strategy to adopt to achieve growth (Sapienza and Gupta, 1994). If firm growth is not achieved, CEO turnover will occur if the VC holds the CEO accountable for low growth.

Theory predicts that the empirical relationship between firm growth and CEO turnover is stronger in VC-backed firms compare to non-VC-backed firms. Therefore, we posit the following hypotheses:

H4: director turnover in VC-backed firms is more sensitive to firm growth than in non-VC-backed firms.

H5: director turnover in VC-backed firms is more sensitive to low relative growth than in non-VC-backed firms.

3. Model specification and variables

3.1 Model specification

Hypothesis 1 states that there is a direct relationship between VC-backing and director turnover in portfolio firms. In model 1, this is captured with the *VC* binary variable, equal to one if a portfolio firm has VC backing, zero otherwise. Hypothesis 2 states that director turnover in portfolio firms with VC backing is more sensitive to performance compared to non-VC-backed firms. To test this hypothesis, model 1 includes the interaction term of the *VC* binary variable with our measure of firm performance, industry-adjusted return on assets ($AdjROA_{it-1}$). The performance measure is lagged one period to allow for VCs to observe performance in a period and then act the next period. Formally, to test hypotheses 1 and 2, we estimate the baseline model below:

$$Director\ turnover_{it} = a_i + a_1 VC_{it} + a_2 AdjROA_{it-1} + a_3 VC_{it} * AdjROA_{it-1} + \boldsymbol{a_4} X_{it-1} + v_j + v_t + e_{it} \quad (1)$$

where subscript i indexes firms, j industries and t time. The model includes a set of control variables X measured at time t-1. The definition and construction of all variables is provided in the next section. Our expectation is that the coefficient a_1 is positive (H1) while a_3 is negative (H2) as better performance should be associated with lower turnover. As usual, e_{it} represents the idiosyncratic error term and the remaining terms capture firm, time, and industry specific effects.

To test H3, we estimate a modified version of our baseline model in which we replace the term $VC_{it} * AdjROA_{it-1}$ with interactions of the VC dummy with quartile indicators of the firm performance variable. The model takes the following form:

$$Director\ turnover_{it} = a_i + a_1 VC_{it} + a_2 AdjROA_{it-1} + \boldsymbol{a_3} \sum VC_{it} * AdjROA_{it-1}\text{-}Q_q$$
$$+ \boldsymbol{a_4} X_{it-1} + v_j + v_t + e_{it} \tag{2}$$

where $AdjROA_{it-1}\text{-}Q_q$ denote the quartiles of the performance variable. The remaining variables are as described above.

Our last two hypotheses (H4 and H5) relate director turnover with achievement of growth objectives instead of performance. To test them, we replace *AdjROA* in equations (1) and (2) with *Growth*, and estimate the models below.

$$Director\ turnover_{it} = a_i + a_1 VC_{it} + a_2 Growth_{it-1} + a_3\ VC_{it} * Growth_{it-1}$$
$$+ \boldsymbol{a_4} X_{it-1} + v_j + v_t + e_{it} \tag{3}$$

$$Director\ turnover_{it} = a_i + a_1 VC_{it} + a_2 Growth_{it-1} + \boldsymbol{a_3} \sum VC_{it} * Growth_{it-1}\text{-}Q_q$$
$$+ \boldsymbol{a_4} X_{it-1} + v_j + v_t + e_{it} \tag{4}$$

where all variables are explained below and *Growth* is our proxy of firm growth objectives in terms of sales and number of employees, alternatively.

3.2 Variables

3.2.1 Dependent variable

VC firms could impose board changes in their portfolio firms in a number of ways. These include altering the composition and the size of the board. Our main dependent variable *Director turnover* is the number of directors leaving the firm in year t relative to the board size in year t-1. As standard in the literature (Lehn and Zhao, 2006; Renneboog and Zhao, 2020; Chemmanur et al., 2021), we assume that directors over the age of 65 are likely to relinquish their positions due to retirement instead of being forced to leave.

In a later section, we use additionally the dependent variable *Director change,* defined as an indicator equal to 1 if a director departed from the board in year t, and 0 otherwise. Using the alternative dependent variable allows us to check the robustness of our results and to relate with the existing literature (Chemmanur et al., 2021),

3.2.2 Independent variables

The two variables of interest in model 1, *VC* and *AdjROA,* allow us to test H1 and H2, our first two hypotheses. *VC* is a dummy variable equal to one if the firm is venture capital funded in a given year, and zero otherwise. In line with previous studies (Heger and Tykvova, 2009; Chemmanur et al., 2021), our prediction is that the coefficient a_1 is positive and significant (H1). We proxy firm financial performance by the return on assets (ROA), defined as net profits scaled by total assets. Our final financial performance proxy is an adjusted return on assets (*AdjROA*) that measures a firm's profitability relative to the average ROA in its two-digit SIC code industry. For each firm and year, we subtract the industry average ROA from the firm's ROA. We expect the director turnover and firm performance negative correlation to be stronger in the case of VC-backed firms and use the interaction term *VC*AdjROA* to test our second hypothesis (H2). A negative and significant coefficient a_3 would suggest that director turnover in VC-backed firms is more sensitive to performance relative to non-VC-backed firms.

To measure relative underperformance, we construct four dummies corresponding to the quartiles of the firms' adjusted performance distribution *AdjROA-Qq*, where q = 1,..,4.We use these indicators to replace *AdjROA* and its interaction with *VC* in model 2. This allows us to identify whether the lower part of the performance distribution triggers changes in the executive board. As stated in Hypothesis 3, board changes are expected to be linked with underperformance.

Finally, to examine the relationship between director turnover and growth objectives (H4 and H5) we use the portfolio firms' sales growth, defined as the first difference in the natural logarithm of sales between two successive years. We construct employment growth similarly.

The timing and causality of the effects of VC director appointments and replacements on performance are indeed complex issues that can pose challenges in empirical research. Adequately capturing these effects depends on how variables are constructed, the availability of data, and the underlying dynamics of director appointments and turnover. However, due to the data limitation, we can only use lagged variable to reduce such problem.

3.2.3 Control variables

We control for a set of variables known to influence board turnover. Organisational size is often used as an indicator of firm structure and capacity and may predict turnover likelihood (Stewart and Diebold, 2017). We proxy firm size with the firm's total assets. *Firm age* measures the time elapsed since the portfolio firms' incorporation date. Another set of variables captures board characteristics. *Director tenure* is the average number of years that all directors have served on that board. The overall experience of the board is proxied by the variable *Director age*, given by the average age of all directors on the board. *Board size* is the total number of directors on the firm's board. All control variables are measured in year *t-1* to alleviate endogeneity concerns and are expressed in logarithmic form.

4. Data

4.1 Sources and sample construction

Our dataset is constructed using several data sources. We hand collect data about VC investments and their characteristics from Thomson One. Our sample includes only first-time VC investments for portfolio companies located in the UK. One of the largest and most mature in Europe, the VC industry in the UK accounts for approximately 40 percent of total annual private equity deals (Cressy et al., 2014). Relative to the VC market in US, however, the UK VC market has attracted less attention from empirical papers (Bellavitis et al., 2014).

We manually match in information on financial performance and board of directors' characteristics from the FAME database. From the 2320 VC investments identified in Thomson One, we can track the names of 700 firms in FAME over the period 2009 to 2019. Our sample shrunk because of no financial information available in FAME. To make sure we identify exactly the same firm across the two databases, we require that the name-matched firms have identical information regarding location (city and postcode); the same business description and industry; and the founding date precedes the incorporation date. Imposing these restrictions reduces our sample to 478 VC funded companies with available financial and board of directors' information. We drop firms with only one year of data. As our interest is in entrepreneurial firms, we exclude companies that went public prior or after VC investment since public firms may have different structures like board of directors. Corporate VC investments are excluded as well because they have different goals and structures such as longer investment durations compared to other VCs (Milosevic, 2018). Our final sample consists of 401 VC portfolio firms.

To establish a control group that involves non-VC financed companies, we use a matching procedure inspired by Cumming et al. (2020) and Guo and Jiang (2013). From the pool of companies available in FAME, each matched control company meets the following five criteria: 1) it has the same two-digit SIC code industry as the VC portfolio firm; 2) is located in the same postal region[7]; (3) ROA; 4) total assets; 5) incorporation date (age). Matching is performed on characteristics before the first VC investment to avoid them being affected by VC investment. Using this procedure, we match (with replacement) up to five control firms for as many VC backed firms as possible. Where a VC portfolio firm attracts more than five matches, we retain the five closest matches in terms of their propensity scores. We end up with a sample of 261 VC portfolio companies and 1241 control firms. VC sample is further reduced because of no matched control sample. On average, each VC portfolio firm

[7] The postal region classification in FAME includes London Outer/Inner, Scotland, East Midlands, Yorkshire & Humberside, Southern and so on.

is matched with 4.8 non-VC-financed peers. Director turnover in the control sample may be influenced by firm performance and market conditions. For example, in response to market conditions, such as mergers, acquisitions, or changes in business models, companies might opt for director changes to align with new strategic directions.

Table 1 provides the balancing tests and shows that there are no significant differences between the VC backed and control firms after matching.

4.2 Summary statistics

We present in Table 2 the industry (two-digit SIC level) composition of our sample. It is not surprising to observe that, among the 13 economic sectors, a large proportion of the sampled firms operate in Information and telecommunication, followed by Professional, scientific and technical activities. A sizeable percentage of firms, however, are in other economic sectors such as manufacturing or wholesale and retail trade.

Table 3 presents summary statistics and the pairwise correlation matrix. Panel A reports the number of observations, mean values, and standard deviations for all firms and separately by VC-funding. Compared to the control group, VC-backed companies experience significantly higher level of director turnover. This is consistent with the assumption that venture capitalists provide monitoring services and actively get involved in the governance of their portfolio firms. Since we used propensity score matching to establish the control sample, there are no significant differences between the two groups of firms in terms of adjusted ROA, sales growth, total assets, firm age, and board size. However, VC-funded firms can hire more employees than non-VC-funded ones. On average, directors in companies without VC backing are around 2.7 years older than directors in portfolio firms. Average director tenure of VC portfolio firms is approximately 4.8 years, while directors in non-VC-backed counterparts are longer (5.2 years) serving on the board.

The correlation coefficients in Panel B are small in magnitude and generally statistically significant at 1% level. They also carry the expected sign. Consistent with hypothesis 1, VC-backing and director turnover are positively correlated. Director turnover correlates negatively with firm performance (*AdjROA*) implying that underperforming directors are likely to leave. The variance inflation factor (VIF) of 1.16 suggests that multicollinearity should not be a concern.

Table 4 aims to identify the relationship between firm *relative* performance distribution and director turnover. In the top part of the table, we construct four dummies corresponding to the quartiles of the firms' adjusted relative performance distribution. It is apparent that director turnover is higher for all firms, irrespective of VC-backing, when relative firm performance is lower: across columns, director turnover decreases as we move down the columns along higher performance quartiles. Importantly, looking at the lowest performance quartile, VC-backed firms have 6.4 percentage points higher turnover than their non-VC-financed peers. The difference remains economically (3 percentage points) and statistically significant at the second quartile. The statistically insignificant difference at the third quartile seems to suggest that venture capitalists do not initiate board changes at such performance levels above the industry average. In contrast, at the highest quartile we notice an increase in director turnover for VC-backed firms. This may be consistent with job-hopping of high performing directors.

The rest of the table contrasts director turnover across quartiles of firm growth for firms with and without VC backing. A similar pattern emerges. For both sales and employment growth distributions, director turnover is significantly higher for VC-backed firms relative to firms without VC backing and declines as we move towards higher growth quartiles. Overall, the univariate analysis provides some initial evidence supporting our hypotheses.

To provide a visual account of director turnover around the time of the first VC investment, we use an event study framework. Specifically, we show in Figure 1 the β coefficients and the 95 percent confidence intervals estimated from the equation:

$$\textit{Director turnover} = \beta T_{it} + a_i + \varepsilon_{it} \tag{5}$$

where the event time indicator variable T equals 1 if an entrepreneurial firm received VC investments in that calendar year. The x axis spans five years before and after VC investment occurs. We control for firm and year fixed effects and cluster standard errors at firm level. The year before VC investment is used as the base period and we normalise its corresponding coefficient to 0. The figure generally supports the parallel trends assumption. Director turnover levels are generally higher post VC investment. Compared to the base year, director turnover increases the year in which portfolio firms receive VC financial injections and peaks one year later.

5. Empirical results

Table 5 presents our fixed effects estimates of equation 1, controlling for firm-, industry- and time-specific effects, as specified. Standard errors are clustered at the firm level and the corresponding t-statistics are reported in parentheses. The first column tests our first hypothesis only. In column 2, we add the interaction term *VC*AdjROA* to test our second hypothesis that turnover is related with portfolio firm performance in VC-backed firms. The last column controls additionally for industry fixed effects. Across columns, we notice that VC backing attracts a positive and highly significant coefficient. These findings are economically significant as well. Looking at the last column, VC portfolio firms experience, on average, 5.8 percentage points higher director turnover than firms without VC backing. This confirms our hypothesis H1. Turning attention to columns 2 and 3, we find a significantly negative estimated parameter on the interaction term *VC*AdjROA*; it indicates that director turnover in VC-funded companies is associated with higher performance-turnover sensitivity than their non-VC-funded counterparts. This provides support for our second hypothesis (H2).

Most coefficients on the control variables are significant and have the expected sign. While the average board age does not seem to matter, both the size and the tenure of the board correlate positively with turnover. The longer the director tenure, the more likely the directors relinquish their position on the board. Corporate boards tend to become less stable as board size increases. One possible reason is that conflicts may arise when new directors are appointed (Brown et al., 2017). Additionally, competition is fiercer in larger boards and original directors are more likely to be replaced by new members. Finally, both firm size and age correlate negatively with director turnover. Larger and older companies experience lower turnover; they have had the time and resources to reach a more compatible and stable board.

Having established that VC firms punish the directors of their portfolio firms for poor performance, now we investigate in detail the relative performance distribution that triggers director change. To this end, we replace the performance variable *AdjROA* in equation 1 with its previously defined quartile indicators. Columns 1-4 in Table 6 include one of the quartiles and its interaction with the *VC* dummy; the last two columns include them all and use the first (fourth) quartile as the reference group. Our results suggest highly performing portfolio firms are associated with lower turnover. VC firms seem to punish directors of their portfolio firms only when their performanceis in the lowest quartile. Low performing firms are likely to experience higher board turnover when they are VC-backed relative to firms without VC-backing.

5.1 Portfolio firm growth objective

Now we estimate equations (3) and (4) which allow us to test our hypotheses linking director turnover and portfolio firm growth objectives. The results in Table 7 show that both sales (columns 1-3) and employment growth (columns 4-6) are negatively associated with director turnover. Moreover, VC portfolio firms witness higher turnover when sales growth and employment growth are low. These results provide support for Hypothesis 4. Portfolio firms' growth is crucial in the process of VC monitoring as it is closely related to VC exit and success. VCs are inclined to participate in the follow-on funding only if their backed firms meet the milestones. Otherwise, directors are likely to be changed such that the firm achieves faster future growth (Standaert et al., 2022).

Finally, we test whether the director turnover-growth sensitivity is higher when portfolio firms underperform as stated in Hypothesis 5. Table 7 Panels B and C provide some interesting insights. Director turnover is significantly higher in VC-backed firms in the bottom three quartiles compared to the highest quartile of sales growth. The economic magnitude ranges between 6-15 percentage points. In contrast, VC-backed firms in the bottom three quartiles of employment growth do not have significantly different director turnover compared to non-VC-backed firms. These findings suggest that it is sales growth that matters to VCs, not employment growth.

6. Extended analysis and robustness tests

This section presents the results of our extended analysis and a series of robustness tests.

6.1 Portfolio firm and VC heterogeneity

In this section, we perform several cross-sectional tests. Our objective is to evaluate whether heterogeneity across VC investment type or stage at which funding occurs has a differential impact on director turnover in portfolio firms. The first dimension we consider is the investment stage at which VC funding occurs. To this end, we define two new indicators *Early stage* and *Expansion stage* corresponding to the investment stage at which VC investment occurs. Young ventures in the early stage primarily focus on the research and development of innovative products. At this stage, technically oriented directors are decisive for firm survival and success. In contrast, later-stage start-ups have already developed their technological products. They would pay more attention to commercialisation; therefore, managerial know-how becomes more crucial than technical expertise. This is consistent with the results reported in column 1 of Table 8, which suggest higher director turnover for expansion stage investment. In what regards firm performance, this seems to matter more for director turnover in both VC investment stages relative to firms without VC funding.

Now we shift focus to VC characteristics. In column 2, we distinguish *International VC* (equal 1 if investment involves at least one foreign VC, 0 otherwise) from *Domestic VC* (equal 1 if investment involves only domestic VCs, 0 otherwise). International and domestic VCs have similar incentives to initiate board changes partly because they value the quality of the board. Portfolio firm performance in terms of ROA seems to be a stronger driver of director turnover for domestic VC investments compared to non-VC backed firms.

Finally, in column 3 we capture the size of the VC team with two dummy variables: *VC syndication* (1 if investment involves two or more VC investors, 0 otherwise) and *VC non-syndication* (1 if the investment involves only one VC investor, 0 otherwise). VC investors could make turnover decisions together and appoint directors who are able to represent their overall benefits. When an investment is syndicated, a syndicate leader is likely to be selected and responsible for interacting with portfolio firms. Thereby, VC syndicate may be more actively involved with their backed firms (e.g., provide more intensive monitoring). The number of investors involved in a VC deal does not influence much the director turnover - performance relationship; this is stronger for both VC syndicates and single VC investors relative to firms without VC backing.

6.2 Fractional response model

Our dependent variable, director turnover, is bounded between 0 and 1 by construction. Using a linear estimator could yield several estimation issues such as: predicted values lie outside the natural interval; the predicted constant partial effects are incompatible with bounded dependent variables (Gallani et al., 2015). To reduce these estimation problems, we now use the fractional response model. We follow Wooldridge (2011) and incorporate the correlated random effects (CRE) in the fractional response model developed by Papke and Wooldridge (2008), which is appropriate for balanced panels only. Similar to the fixed-effects (FE) estimator, the CRE model accounts for firm heterogeneity by including the time averages of all time-varying covariates. Additionally, the CRE model allows inclusion of time-invariant variables and addresses the unbalanced aspect of our panel data in the nonlinear fractional response model.

As with all nonlinear models, our interest lies not in the estimated coefficients but in the marginal effects. In Tables 9 and 10, we present the average marginal effects obtained from the fractional response model. Standard errors are clustered at firm level. In Table 9, we find that VCs have a significantly positive impact on director turnover and lower performance (*AdjROA*) makes VC-backed firms experience higher director turnover compared to non-VC-backed peers. The last six columns in Table 9 report consistent results for firm growth. They are all in line with those reported in Tables 5 and 7, and provide support for hypotheses H1, H4 and H5.

6.3 Alternative dependent variable

Our dependent variable so far has been the proportion of directors that leaves the board each year. We now use a dichotomous variable *Director change* set equal to 1 if a member departed from the board in year t, and 0 otherwise. This allows us to relate to the existing literature (Chemmanur et al, 2021). Given the binary nature of the dependent variable, we use the probit estimator to estimate the model including all independent variables as defined earlier, industry and time fixed effects. Once again, to control for firm heterogeneity and the unbalanced aspect of our panel data, we use the correlated random effects (CRE) probit model. Table 10 reports the average marginal effects. The results suggest that VC-funded firms are roughly 6% more likely to initiate board changes than non-VC-funded ones. The likelihood of observing changes in VC-sponsored firms increases relative to non-VC-sponsored peers by 8.4 percentage points as firm performance worsens (column 3). When we use our measures for portfolio firm growth, our results in columns 4-9 confirm that VC portfolio firms are more likely to change directors than non-VC-backed firms when sales and employment growth are low.

6.4 Alternative matching

Our results might be sensitive to the construction of the matched control group. We address this issue by adjusting our matching algorithm. Specifically, we now construct the matched control group as follows: 1) we identify control firms within a 50% bracket of the target company in terms of ROA, total assets and age if they have the same two-digit SIC code and location; 2) if a VC portfolio firm attracts more than five matches, we retain the five closest matches based on the sum of the squares of the differences between the control and treated firms' ROA, total assets and age. We find that 259 VC-funded companies are matched with 1082 non-VC-funded companies. Appendix Table A1 shows the t-tests for the differences in means between VC-funded and non-VC-funded companies using the alternative matching. We estimate all models again on the newly matched sample and report the results in Appendix Tables A2 and A3. Using the alternative matching criteria produces results qualitatively similar to those reported in Tables 5 and 6.

6.5 Alternative measure of relative performance

Our portfolio firm performance measure is calculated relative to the average (two-digit SIC) industry performance. We construct it relative to annual industry median value instead. The results in Appendix Table A4 are quantitatively and qualitatively similar to those reported in Table 5.

7. Conclusions

In this paper, we have used hand-collected data about first-time VC investments during the period 2009-2019 in portfolio companies located in the UK to conduct the first large-sample study of the relationship between VC-backing and director turnover in portfolio firms. Our results showed that VC portfolio companies witness higher director turnover than firms without VC backing. Moreover, director turnover in VC portfolio companies is more sensitive to performance and growth than in non-VC-funded companies. Our detailed analysis suggests that VC-funded firms experience higher director turnover when their relative performance is in the bottom quartile within their industry. Our results also reveal that VC firms trigger board director changes when portfolio firms underperform in terms of sales growth.

VCs play a crucial role in monitoring portfolio firms. Corporate governance mechanisms and effectiveness in VC-backed firms are different than in other private firms. VCs actively monitor the board of directors and even discipline unqualified top managers. This result has implications for board members in VC-backed firms because they may suffer from pressures from VC monitoring and have more incentives to enhance firm performance to keep their job safe. The decisions to change board composition are contingent on the firm performance for VC-backed firms. The results would be helpful for board of directors in VC-funded firms to realise the preferences of VCs. In the case of VC financial injections, board members of VC portfolio companies should be in line with VC goals and interests in order to maintain their board seat.

This research is not without limitations. A common caveat in the corporate governance literature and board turnover is the inability to completely separate voluntary and involuntary director departure (Arthaud-Day et al., 2006). Our analysis has not examined the relationship between VCs' human capital, such as prior business experience and education experience, and director turnover. Experienced VCs could be more prudent in making turnover decisions. We leave this for future research. Additionally, director turnover measurements might not distinguish between executive and non-executive directors. Non-executive directors might have limited direct involvement in day-to-day operations and strategic decision-making, potentially affecting the interpretation of turnover's impact on performance.

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Figures

Figure 1. Director turnover around VC investment

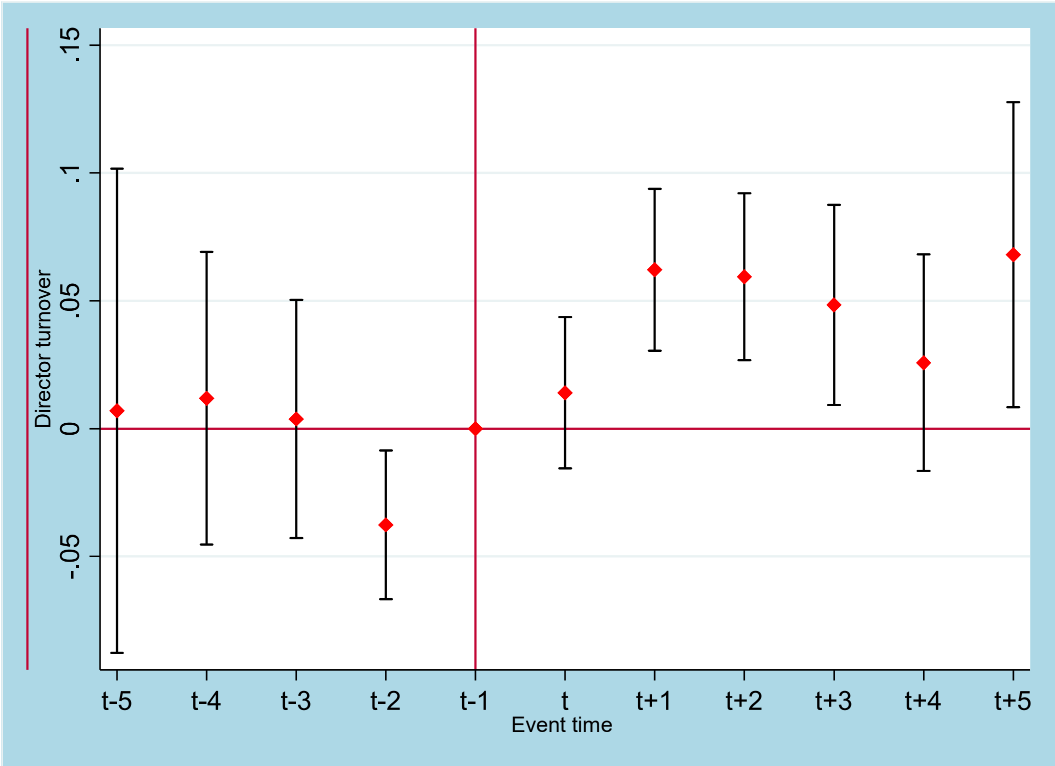

Table 1. Balancing tests for sample construction

Panel A: PSM analysis				
Difference in means			0.029	
Standard errors			0.017	
T-statistics			1.715	

Panel B: balancing test				
Variables	Sample	Treated	Control	P-value
ROA	Unmatched	-28.931	7.076	0.000
	Matched	-28.931	-25.487	0.439
Total asset (£ millions)	Unmatched	7.994	202.923	0.000
	Matched	7.994	7.355	0.453
Age	Unmatched	8.697	18.123	0.000
	Matched	8.697	8.186	0.425

Table 2. Industry composition (two-digit SIC level)

Industry	VC-backed firms		Non-VC-backed firms		Whole sample	
	Obs.	%	Obs.	%	Obs.	%
Manufacturing	124	10.2	1294	13.2	1418	12.9
Electricity, gas, steam and air conditioning supply	16	1.3	108	1.1	124	1.1
Water supply, sewerage and waste management	9	0.7	106	1.1	115	1.1
Wholesale and retail trade	123	10.1	925	9.4	1048	9.5
Accommodation and food service activities	18	1.5	130	1.3	148	1.3
Information and communication	396	32.5	2802	28.6	3198	29.0
Finance and insurance activities	80	6.6	554	5.6	634	5.7
Professional, scientific and technical activities	252	20.7	2034	20.7	2286	20.7
Administrative and support service activities	111	9.1	936	9.5	1047	9.5
Education	16	1.3	152	1.6	168	1.5
Human health and social work activities	48	3.9	519	5.3	567	5.1
Arts, entertainment and recreation	17	1.4	180	1.8	197	1.8
Other service activities	9	0.7	80	0.8	89	0.8
Total	1219	100	9820	100	11039	100

Table 3. Summary statistics and correlation matrix
Panel A. Descriptive statistics

	Whole sample			VC portfolio firms			Non-VC-financed firms			Difference in means	t-test
	N	Mean	S.D	N	Mean	S.D	N	Mean	S.D		
Director turnover	11039	0.132	0.230	1219	0.171	0.248	9820	0.127	0.228	0.044	5.834***
AdjROA	11039	0.000	0.867	1219	-0.023	0.709	9820	0.003	0.885	-0.026	-1.184
Sales growth	8582	0.116	0.532	917	0.146	0.503	7665	0.112	0.536	0.033	1.892*
Employment growth	7846	0.084	0.386	807	0.139	0.335	7039	0.078	0.391	0.061	4.780***
Total asset (£ millions)	11039	11.609	63.407	1219	11.096	14.299	9820	11.673	67.039	-0.577	-0.730
Director age	11039	50.889	8.057	1219	48.472	6.109	9820	51.189	8.217	-2.717	-14.033***
Firm age	11039	10.559	9.489	1219	10.683	6.649	9820	10.544	9.785	0.139	0.648
Board size	11039	4.532	2.914	1219	4.567	2.094	9820	4.528	2.999	0.039	0.591
Director tenure	11039	5.176	4.048	1219	4.840	2.516	9820	5.218	4.197	-0.378	-4.519***

Notes: The table reports the number of observations, mean values, and standard deviations for the whole sample and separately for VC-backed and non-VC-backed firms. The last column reports the t-statistic for the equality of means for the two categories of firms. * p<0.1, ** p<0.05, *** p<0.01.

Panel B. Correlation matrix

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	Director turnover	1.00									
(2)	AdjROA	-0.046*	1.00								
(3)	Sales growth	-0.015	-0.001	1.00							
(4)	Employment growth	-0.032	-0.005	0.329*	1.00						
(5)	Total assets	0.029	0.015	0.013	0.013	1.00					
(6)	Director age	-0.109*	0.011	-0.046*	-0.026	-0.049*	1.00				
(7)	Firm age	-0.016	0.018	-0.096*	-0.082*	0.024	0.224*	1.00			
(8)	Board size	0.027	-0.003	-0.027	-0.021	0.029	0.154*	0.138*	1.00		
(9)	Director tenure	-0.190*	0.028	-0.057*	-0.022	-0.038*	0.315*	0.412*	-0.041*	1.00	
(10)	VC	0.059*	-0.010	0.019	0.048*	-0.003	-0.106*	0.005	0.004	-0.029	1.00

Note: * denotes significance at the 0.01 level.

Table 4. Director turnover and relative performance and growth distribution

Turnover	Whole sample	VC portfolio firms	Non-VC-financed firms	t-test
AdjROA-Q1	0.157	0.212	0.148	4.554***
	(0.249)	(0.267)	(0.234)	
AdjROA-Q2	0.129	0.157	0.127	2.574**
	(0.226)	(0.236)	(0.225)	
AdjROA-Q3	0.120	0.113	0.121	-0.289
	(0.221)	(0.208)	(0.224)	
AdjROA-Q4	0.119	0.159	0.113	3.381***
	(0.221)	(0.246)	(0.216)	
Sales growth-Q1	0.179	0.225	0.174	2.263**
	(0.246)	(0.281)	(0.242)	
Sales growth-Q2	0.121	0.210	0.114	3.902***
	(0.210)	(0.277)	(0.202)	
Sales growth-Q3	0.099	0.149	0.094	3.041***
	(0.193)	(0.204)	(0.192)	
Sales growth-Q4	0.118	0.127	0.117	0.792
	(0.215)	(0.205)	(0.217)	
Employment growth-Q1	0.165	0.210	0.161	2.112**
	(0.244)	(0.250)	(0.243)	
Employment growth-Q2	0.116	0.205	0.113	2.930***
	(0.203)	(0.244)	(0.201)	
Employment growth-Q3	0.117	0.179	0.110	3.428***
	(0.211)	(0.259)	(0.204)	
Employment growth-Q4	0.114	0.151	0.106	2.893***
	(0.208)	(0.238)	(0.200)	

Note: The table presents summary statistics for *Director turnover* across quartiles of portfolio firm performance (*AdjROA*)and growth in terms of *Sales* and *Employment,* respectively. The last column reports the t-statistic for the equality of means of *Director turnover* for VC-backed vs. non-VC-backed firms. * p<0.1, ** p<0.05, *** p<0.01.

Table 5. Director turnover and portfolio firm performance

	(1)	(2)	(3)
VC	0.053***	0.056***	0.058***
	(2.99)	(3.15)	(3.18)
AdjROA	-0.008*	-0.002	-0.001
	(-1.84)	(-0.37)	(-0.34)
VC*AdjROA		-0.071***	-0.070***
		(-3.66)	(-3.63)
Director tenure	0.070***	0.070***	0.071***
	(9.22)	(9.24)	(9.10)
Director age	0.077	0.074	0.079
	(1.48)	(1.45)	(1.49)
Board size	0.084***	0.084***	0.083***
	(6.44)	(6.38)	(6.17)
Total assets	-0.008*	-0.009*	-0.011**
	(-1.80)	(-1.94)	(-2.31)
Firm age	-0.069***	-0.069***	-0.064***
	(-5.32)	(-5.37)	(-4.68)
Constant	-0.163	-0.142	-0.091
	(-0.77)	(-0.69)	(-0.42)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	No	No	Yes
N	9169	9169	9169
Adj. R-sq	3.33%	3.75%	4.30%

Note: This table presents estimated coefficients (t-statistics in parentheses). The dependent variable is *Director turnover* measured by the number of directors who leave the firm in year t divided by the board size in year t-1. *VC* is equal to one if the firm receives VC investment in a given year, and zero otherwise. *AdjROA* is estimated by subtracting the (two-digit SIC code) industry average ROA each year from each firm's ROA. Controls include total assets, board size, firm age and director age. Heteroskedasticity-robust standard errors are clustered at firm level. * p<0.1, ** p<0.05, *** p<0.01.

Table 6. Director turnover and portfolio firm relative performance

	(1)	(2)	(3)	(4)	(5)	(6)
VC	0.036*	0.056***	0.065***	0.058***	0.104***	0.042*
	(1.92)	(3.14)	(3.28)	(2.83)	(3.83)	(1.92)
AdjROA-Q1	0.017**					0.026**
	(2.03)					(2.49)
VC* AdjROA-Q1	0.066***					0.063**
	(2.70)					(2.12)
AdjROA-Q2		-0.004			-0.014	0.012
		(-0.54)			(-1.45)	(1.20)
VC* AdjROA-Q2		-0.012			-0.054*	0.009
		(-0.51)			(-1.87)	(0.29)
AdjROA-Q3			0.004		-0.012	0.014
			(0.57)		(-1.15)	(1.53)
VC* AdjROA-Q3			-0.042*		-0.084***	-0.022
			(-1.88)		(-2.82)	(-0.83)
AdjROA-Q4				-0.017**	-0.026**	
				(-2.06)	(-2.49)	
VC* AdjROA-Q4				-0.010	-0.063**	
				(-0.43)	(-2.12)	
Director tenure	0.072**	0.071***	0.071***	0.071***	0.072***	0.072***
	(9.15)	(9.06)	(9.13)	(9.09)	(9.21)	(9.21)
Director age	0.082	0.081	0.083	0.080	0.083	0.083
	(1.55)	(1.51)	(1.55)	(1.50)	(1.56)	(1.48)
Board size	0.083***	0.085***	0.085***	0.084***	0.083***	0.083***
	(6.12)	(6.27)	(6.27)	(6.24)	(6.12)	(6.12)
Total assets	-0.010**	-0.012**	-0.012**	-0.012**	-0.010**	-0.010**
	(-2.08)	(-2.53)	(-2.53)	(-2.58)	(-2.11)	(-2.11)
Firm age	-0.065***	-0.063***	-0.064***	-0.064***	-0.066***	-0.066***
	(-4.73)	(-4.58)	(-4.68)	(-4.65)	(-4.82)	(-4.82)
Constant	-0.120	-0.091	-0.099	-0.078	-0.001	-0.128
	(-0.55)	(-0.41)	(-0.45)	(-0.35)	(-0.00)	(-0.59)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	9169	9169	9169	9169	9169	9169
Adj. R-sq	4.10%	3.90%	3.90%	3.90%	4.10%	4.10%

Note: This table presents estimated coefficients (t-statistics in parentheses). The dependent variable is *Director turnover* measured by the number of directors who leave the firm in year t divided by the board size in year t-1. *VC* is equal to one if the firm receives VC investment in a given year, and zero otherwise. *AdjROA* is estimated by subtracting the (two-digit SIC code) industry average ROA each year from each firm's ROA. Across columns, we use interactions of *VC* with different quartiles of *AdjROA*. See also notes to Table 6. * p<0.1, ** p<0.05, *** p<0.01.

Table 7. Portfolio firms' growth and director turnover

Panel A. Director turnover and growth

	(1)	(2) Sales growth	(3)	(4)	(5) Employment growth	(6)
VC	0.044*	0.052*	0.050*	0.048	0.055*	0.051*
	(1.74)	(1.97)	(1.89)	(1.63)	(1.88)	(1.71)
Sales growth	-0.023***	-0.017***	-0.017***			
	(-3.96)	(-3.03)	(-3.04)			
VC*Sales growth		-0.126***	-0.121***			
		(-3.71)	(-3.55)			
Employment growth				-0.034***	-0.028***	-0.032***
				(-3.93)	(-3.40)	(-3.77)
VC* Employment growth					-0.098**	-0.099*
					(-1.99)	(-1.96)
Director tenure	0.100***	0.100***	0.102***	0.096***	0.096***	0.099***
	(11.08)	(11.10)	(11.14)	(10.57)	(10.55)	(10.79)
Director age	0.075	0.071	0.073	0.137**	0.135*	0.137*
	(1.18)	(1.12)	(1.13)	(2.00)	(1.96)	(2.03)
Board size	0.110***	0.110***	0.110***	0.111***	0.110***	0.109***
	(6.82)	(6.82)	(6.78)	(6.85)	(6.76)	(6.62)
Total assets	-0.006	-0.006	-0.008	-0.010	-0.009	-0.011
	(-0.91)	(-0.97)	(-1.31)	(-1.47)	(-1.42)	(-1.56)
Firm age	-0.101***	-0.100***	-0.095***	-0.107***	-0.105***	-0.101***
	(-5.18)	(-5.12)	(-4.39)	(-5.44)	(-5.37)	(-4.67)
Constant	-0.185	-0.168	-0.094	-0.370	-0.367	-0.273
	(-0.71)	(-0.65)	(-0.35)	(-1.29)	(-1.28)	(-0.96)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
N	7072	7072	7072	6476	6476	6476
Adj. R-sq	5.50%	5.90%	6.90%	5.60%	5.70%	6.60%

Note: This table presents estimated coefficients (t-statistics in parentheses). The dependent variable is *Director turnover* measured as the number of directors who leave the firm in year t divided by the board size in year t-1. *VC* is equal to one if the firm receives VC investment in a given year, and zero otherwise. *Sales growth* is the first difference of the logarithm of sales between two successive years. *Employment growth* is calculated similarly. See also notes to Table 6. * p<0.1, ** p<0.05, *** p<0.01.

Panel B. Director turnover and relative sales growth performance

	(1)	(2)	(3)	(4)	(5)	(6)
VC	0.029	0.016	0.045	0.059**	0.060*	-0.053*
	(1.09)	(0.62)	(1.63)	(2.29)	(1.65)	(-1.70)
Sales growth-Q1	0.042***					0.047***
	(5.51)					(5.06)
VC* Sales growth-Q1	0.051					0.112***
	(1.57)					(3.27)
Sales growth-Q2		0.002			-0.030***	0.017**
		(0.31)			(-3.51)	(2.03)
VC* Sales growth-Q2		0.090***			0.038	0.151***
		(2.66)			(0.91)	(4.44)
Sales growth-Q3			-0.023***		-0.050***	-0.002
			(-3.65)		(-5.58)	(-0.29)
VC* Sales growth-Q3			-0.008		-0.048	0.064**
			(-0.31)		(-1.36)	(2.38)
Sales growth-Q4				-0.022***	-0.047***	
				(-2.96)	(-5.06)	
VC* Sales growth-Q4				-0.103***	-0.112***	
				(-4.49)	(-3.27)	
Director tenure	0.102**	0.102***	0.102***	0.102***	0.102***	0.102***
	(11.32)	(11.06)	(11.17)	(11.03)	(11.29)	(11.29)
Director age	0.072	0.072	0.075	0.071	0.072	0.072
	(1.13)	(1.12)	(1.17)	(1.10)	(1.12)	(1.12)
Board size	0.110***	0.110***	0.110***	0.109***	0.109***	0.109***
	(6.81)	(6.72)	(6.78)	(6.69)	(6.76)	(6.76)
Total assets	-0.008	-0.010	-0.009	-0.009	-0.007	-0.007
	(-1.30)	(-1.56)	(-1.49)	(-1.40)	(-1.18)	(-1.18)
Firm age	-0.091***	-0.087***	-0.085***	-0.093***	-0.092***	-0.092***
	(-4.26)	(-4.03)	(-3.93)	(-4.30)	(-4.28)	(-4.28)
Constant	-0.120	-0.089	-0.102	-0.073	-0.081	-0.129
	(-0.46)	(-0.33)	(-0.38)	(-0.28)	(-0.31)	(-0.49)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7072	7072	7072	7072	7072	7072
Adj. R-sq	7.10%	6.40%	6.40%	7.00%	7.80%	7.80%

Note: This table presents estimated coefficients (t-statistics in parentheses). The dependent variable is *Director turnover* measured as the number of directors who leave the firm in year t divided by the board size in year t-1. *VC* is equal to one if the firm receives VC investment in a given year, and zero otherwise. *Sales growth* is the first difference of the logarithm of sales between two successive years. Across columns we use interactions of *VC* with different quartiles of *Sales growth*. See also notes to Table 6. * p<0.1, ** p<0.05, *** p<0.01.

Panel C. Director turnover and relative employment growth performance

	(1)	(2)	(3)	(4)	(5)	(6)
VC	0.034	0.046	0.042	0.052*	0.067*	0.014
	(1.05)	(1.56)	(1.32)	(1.71)	(1.87)	(0.37)
Employment growth-Q1	0.024***					0.043***
	(3.14)					(4.54)
VC* Employment growth-Q1	0.040					0.054
	(1.19)					(1.36)
Employment growth-Q2		0.008			-0.011	0.031***
		(1.27)			(-1.31)	(3.67)
VC* Employment growth-Q2		-0.001			-0.032	0.022
		(-0.05)			(-0.76)	(0.59)
Employment growth-Q3			-0.005		-0.023**	0.020**
			(-0.73)		(-2.41)	(2.27)
VC* Employment growth-Q3			0.013		-0.020	0.034
			(0.39)		(-0.49)	(0.84)
Employment growth-Q4				-0.031***	-0.043***	
				(-4.20)	(-4.54)	
VC* Employment growth-Q4				-0.038	-0.054	
				(-1.20)	(-1.36)	
Director tenure	0.099**	0.099***	0.099***	0.099***	0.100***	0.100***
	(10.81)	(10.66)	(10.68)	(10.76)	(10.86)	(10.86)
Director age	0.131*	0.134**	0.135**	0.132*	0.130*	0.130*
	(1.93)	(1.98)	(1.99)	(1.96)	(1.92)	(1.92)
Board size	0.111***	0.110***	0.110***	0.108***	0.109***	0.109***
	(6.67)	(6.57)	(6.61)	(6.51)	(6.55)	(6.55)
Total assets	-0.012*	-0.012*	-0.012*	-0.012*	-0.012*	-0.012*
	(-1.68)	(-1.69)	(-1.69)	(-1.75)	(-1.69)	(-1.69)
Firm age	-0.097***	-0.096***	-0.096***	-0.098***	-0.099***	-0.099***
	(-4.39)	(-4.34)	(-4.33)	(-4.49)	(-4.53)	(-4.53)
Constant	-0.256	-0.262	-0.261	-0.242	-0.225	-0.268
	(-0.90)	(-0.92)	(-0.91)	(-0.85)	(-0.79)	(-0.94)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6476	6476	6476	9169	6476	6476
Adj. R-sq	6.40%	6.10%	6.00%	6.50%	6.60%	6.60%

Note: This table presents estimated coefficients (t-statistics in parentheses). The dependent variable is *Director turnover* measured as the number of directors who leave the firm in year t divided by the board size in year t-1. *VC* is equal to one if the firm receives VC investment in a given year, and zero otherwise. *Employment growth* is the first difference in the number of employees (logarithm) between two successive years. Across columns we use interactions of *VC* with different quartiles of *Employment growth*. See also notes to Table 6. * p<0.1, ** p<0.05, *** p<0.01.

Table 8. Additional analysis

	(1)	(2)	(3)
Early stage	0.034		
	(1.61)		
Early stage* AdjROA	-0.001**		
	(-2.50)		
Expansion stage	0.033**		
	(2.08)		
Expansion stage* AdjROA	-0.000*		
	(-1.84)		
International VC		0.036*	
		(1.94)	
International VC* AdjROA		-0.000	
		(-0.65)	
Domestic VC		0.030*	
		(1.84)	
Domestic VC*AdjROA		-0.001***	
		(-3.12)	
VC syndication			0.036**
			(2.27)
VC syndication* AdjROA			-0.000*
			(-1.89)
VC non-syndication			0.029
			(1.38)
VC non-syndication* AdjROA			-0.001**
			(-2.01)
Adjusted ROA	-0.000	-0.000	-0.000
	(-0.98)	(-0.96)	(-0.99)
Director tenure	0.070***	0.071***	0.070***
	(8.95)	(8.96)	(8.95)
Director age	0.073	0.073	0.076
	(1.38)	(1.38)	(1.43)
Board size	0.087***	0.087***	0.087***
	(6.51)	(6.49)	(6.49)
Total assets	-0.012**	-0.011**	-0.011**
	(-2.47)	(-2.44)	(-2.43)
Firm age	-0.061***	-0.060***	-0.061***
	(-4.39)	(-4.35)	(-4.39)
Constant	0.032	0.025	0.018
	(0.14)	(0.11)	(0.08)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	9169	9169	9169
Adj. R-sq	4.00%	4.10%	4.00%

Note: This table presents estimated coefficients (t-statistics in parentheses). The dependent variable is *Director turnover* measured by the number of directors who leave the firm in year t divided by the board size in year t-1. *Early stage* is a dummy variable which equals to 1 if VC invests in early stage and 0 otherwise. *Expansion stage* is a dummy variable which equals to 1 if VC invests in expansion stage and 0 otherwise. *Domestic VC* is a binary indicator which takes the value of 1 if the investment involves purely domestic VCs and 0 otherwise. *VC syndication* equals 1 if the investment involves two or more VC investors, and 0 otherwise. *VC non-syndication* equals 1 if the investment involves only one VC investor, and 0 otherwise. *International VC* is a binary indicator which takes the value of 1 if the investment involves at least one foreign VC and 0 otherwise. Heteroskedasticity-robust standard errors are clustered at firm level.* $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 9. Portfolio firms' performance and director turnover - fractional response model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VC	0.035***	0.026***	0.033***	0.035***	0.038***	0.037***	0.044***	0.048***	0.047***
	(4.51)	(3.91)	(4.36)	(3.67)	(3.86)	(3.82)	(4.14)	(4.39)	(4.36)
AdjROA	-0.015***	-0.010***	-0.018***						
	(-4.71)	(-3.03)	(-5.63)						
VC*AdjROA		-0.065***	-0.064***						
		(-6.20)	(-6.20)						
Sales growth				-0.029***	-0.029***	-0.030***			
				(-4.83)	(-5.16)	(-5.33)			
VC* Sales growth					-0.076***	-0.078***			
					(-4.21)	(-4.38)			
Employment growth							-0.035***	-0.036***	-0.037***
							(-4.04)	(-4.31)	(-4.46)
VC* Employment growth								-0.083***	-0.090**
								(-2.82)	(-3.07)
Director tenure	-0.051***	-0.051***	-0.048***	-0.054***	-0.054***	-0.050***	-0.054***	-0.054***	-0.049***
	(-15.02)	(-15.05)	(-14.00)	(-14.59)	(-14.55)	(-13.27)	(-14.04)	(-14.03)	(-12.58)
Director age	-0.026*	-0.022	-0.031**	-0.039**	-0.040**	-0.043**	-0.034*	-0.036*	-0.041**
	(-1.67)	(-1.40)	(-1.99)	(-2.23)	(-2.31)	(-2.42)	(-1.88)	(-1.90)	(-2.21)
Board size	0.031***	0.030***	0.024***	0.030***	0.030***	0.027***	0.031***	0.032***	0.027***
	(6.67)	(6.60)	(5.03)	(5.88)	(5.91)	(5.01)	(6.01)	(6.04)	(4.89)
Total assets	0.009***	0.009***	0.010***	0.008***	0.008***	0.009***	0.008***	0.008***	0.009***
	(8.37)	(8.81)	(8.90)	(6.89)	(6.84)	(7.26)	(6.23)	(6.24)	(6.81)
Firm age	0.016***	0.020***	0.019***	0.014***	0.014***	0.016***	0.014***	0.014***	0.015***
	(4.23)	(6.00)	(4.81)	(3.19)	(3.16)	(3.38)	(3.03)	(3.02)	(3.12)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	No	No	No	Yes
Pseudo R2	3.49%	3.64%	4.06%	3.62%	3.66%	4.12%	3.74%	3.76%	4.31%
N	9169	9169	9169	7072	7072	7072	6476	6476	6476
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: This table presents average marginal effects obtained with the fractional response model. The dependent variable is *Director turnover* measured by the number of directors who leave the firm in year t divided by the board size in year t-1. *VC* is equal to one if the firm receives VC investment in a given year, and zero otherwise. *AdjROA* is estimated by subtracting the (two-digit SIC code) industry average ROA each year from each firm's ROA. See also notes to Table 6. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 10. Portfolio firms' performance and director turnover - correlated random effects Probit results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VC	0.066***	0.066***	0.062***	0.101***	0.103***	0.101***	0.123***	0.132***	0.130***
	(4.43)	(4.51)	(4.26)	(5.28)	(5.39)	(5.33)	(6.02)	(6.35)	(6.29)
AdjROA	-0.016**	-0.019**	-0.019**						
	(-2.10)	(-2.47)	(-2.46)						
VC*AdjROA		-0.085***	-0.084***						
		(-4.22)	(-4.19)						
Sales growth				-0.047***	-0.049***	-0.049***			
				(-4.11)	(-4.29)	(-4.30)			
VC* Sales growth					-0.095**	-0.093***			
					(-2.47)	(-2.41)			
Employment growth							-0.062***	-0.067***	-0.067***
							(-3.64)	(-3.92)	(-3.93)
VC* Employment growth								-0.178***	-0.179***
								(-3.24)	(-3.27)
Director tenure	0.071***	0.071***	0.071***	0.078***	0.078***	0.080***	0.073***	0.073***	0.074***
	(6.37)	(6.38)	(6.42)	(5.96)	(5.98)	(6.10)	(5.34)	(5.34)	(5.45)
Director age	0.087	0.084	0.081	0.067	0.066	0.063	0.162*	0.160*	0.160*
	(1.21)	(1.17)	(1.13)	(0.76)	(0.75)	(0.72)	(1.74)	(1.72)	(1.73)
Board size	0.355***	0.355***	0.354***	0.365***	0.366***	0.364***	0.368***	0.367***	0.366***
	(18.21)	(18.21)	(18.20)	(15.50)	(15.50)	(15.49)	(15.10)	(15.06)	(15.01)
Total assets	-0.020**	-0.021***	-0.021***	-0.018*	-0.018*	-0.018*	-0.023**	-0.023**	-0.023**
	(-2.59)	(-2.67)	(-2.68)	(-1.85)	(-1.85)	(-1.89)	(-2.25)	(-2.25)	(-2.28)
Firm age	-0.069***	-0.069***	-0.070***	-0.102***	-0.101***	-0.099***	-0.103***	-0.101***	-0.099***
	(-3.32)	(-3.35)	(-3.37)	(-3.36)	(-3.32)	(-3.28)	(-3.28)	(-3.21)	(-3.16)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes	No	No	Yes
Log likelihood	-4854.388	-4847.543	-4825.463	-3724.427	-3723.646	-3703.174	-3390.546	-3388.208	-3366.512
N	9169	9169	9169	7072	7072	7072	6476	6476	6476
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: This table presents average marginal effects obtained with the correlated random effects probit model. The dependent variable is *Director change* equal to 1 if a member departed from the board in year t, and 0 otherwise. *VC* is equal to one if the firm receives VC investment in a given year, and zero otherwise. See also notes to Table 6. * p<0.1, ** p<0.05, *** p<0.01.

Appendix

Table A1. Alternative matching - t-tests for the differences in means between VC-funded and non-VC-funded companies

	Whole sample			VC portfolio firms			Non-VC-financed firms			Difference in means	T-test
	N	Mean	S.D	N	Mean	S.D	N	Mean	S.D		
Director turnover	10296	0.157	0.259	1210	0.171	0.249	9086	0.156	0.261	0.015	1.985***
AdjROA	10296	0.000	0.680	1210	0.025	0.706	9086	-0.003	0.677	0.028	1.312
Sales growth	7973	0.134	0.581	916	0.146	0.503	7057	0.132	0.590	0.013	0.729
Employment growth	7169	0.085	0.393	804	0.138	0.336	6365	0.078	0.399	0.061	4.706***
Total assets (£ millions)	10296	11.640	31.379	1210	11.128	14.326	9086	11.708	32.991	-0.580	-1.078
Director age	10296	50.479	6.823	1210	48.434	6.113	9086	50.752	6.867	-2.317	-12.201***
Firm age	10296	10.673	7.205	1210	10.722	6.655	9086	10.666	7.275	0.056	0.274
Board size	10296	4.687	2.872	1210	4.564	2.090	9086	4.704	2.960	-0.140	-2.073***
Director tenure	10296	4.788	3.901	1210	4.857	2.517	9086	4.796	4.031	0.061	0.731

Notes: The table reports the number of observations, mean values, and standard deviations for the whole sample and separately for VC-backed and non-VC-backed firms. The last column reports the t-statistic for the equality of means for the two categories of firms. * p<0.1, ** p<0.05, *** p<0.01.

Table A2. Portfolio firms' performance and director turnover - alternative matching

	(1)	(2)	(3)
VC	0.042**	0.047**	0.040**
	(2.28)	(2.52)	(2.11)
AdjROA	-0.018***	-0.010	-0.010
	(-2.87)	(-1.56)	(-1.42)
VC*AdjROA		-0.062***	-0.063***
		(-3.07)	(-3.09)
Director tenure	0.081***	0.081***	0.082***
	(11.52)	(11.47)	(11.21)
Director age	0.107*	0.103*	0.077
	(1.92)	(1.87)	(1.37)
Board size	0.176***	0.176***	0.176***
	(11.64)	(11.58)	(11.39)
Total assets	-0.000	-0.001	-0.002
	(-0.06)	(-0.26)	(-0.36)
Firm age	-0.072***	-0.072***	-0.079***
	(-4.33)	(-4.34)	(-4.36)
Constant	-0.476**	-0.444**	-0.269
	(-2.12)	(-1.99)	(-1.15)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	No	No	Yes
N	8776	8776	8776
Adj. R-sq	3.18%	2.85%	5.90%

Note: This table presents estimated coefficients (t-statistics in parentheses). The dependent variable is *Director turnover* measured by the number of directors who leave the firm in year t divided by the board size in year t-1. *VC* is equal to one if the firm receives VC investment in a given year, and zero otherwise. *AdjROA* is estimated by subtracting the (two-digit SIC code) industry average ROA each year from each firm's ROA. This is the equivalent of Table 6 – results obtained on a sample obtained from an alternative matching. * p<0.1, ** p<0.05, *** p<0.01.

Table A3. Portfolio firms' growth and director turnover - alternative matching

	(1)	(2)	(3)	(4)	(5)	(6)
VC	0.055**	0.063**	0.065**	0.067*	0.075**	0.087***
	(2.10)	(2.26)	(2.18)	(2.26)	(2.54)	(2.71)
Sales growth	-0.017***	-0.012**	-0.13**			
	(-3.34)	(-2.38)	(-2.44)			
VC*Sales growth		-0.127***	-0.123***			
		(-3.72)	(-3.43)			
Employment growth				-0.014	-0.008	-0.009
				(-1.26)	(-0.72)	(-0.74)
VC* Employment growth					-0.111**	-0.114**
					(-2.20)	(-2.20)
Director tenure	0.118***	0.119***	0.122***	0.120***	0.120***	0.122***
	(13.47)	(13.54)	(13.48)	(12.32)	(12.31)	(12.19)
Director age	0.086	0.078	0.058	0.128	0.127	0.107
	(1.18)	(1.08)	(0.80)	(1.62)	(1.60)	(1.35)
Board size	0.224***	0.224***	0.226***	0.221***	0.220***	0.222***
	(11.85)	(11.85)	(11.64)	(11.54)	(11.45)	(11.15)
Total assets	0.003	0.002	0.002	-0.002	-0.002	-0.001
	(0.34)	(0.33)	(0.31)	(-0.24)	(-0.19)	(-0.15)
Firm age	-0.111***	-0.112***	-0.134***	-0.072**	-0.070**	-0.105***
	(-3.76)	(-3.78)	(-3.95)	(-2.37)	(-2.32)	(-2.95)
Constant	-0.480	-0.464	-0.272	-0.651*	-0.652*	-0.404
	(-1.54)	(-1.49)	(-0.84)	(-1.94)	(-1.94)	(-1.17)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
N	6635	6635	6635	5972	5972	5972
Adj. R-sq	8.60%	8.90%	9.10%	8.60%	8.70%	8.70%

Note: This table presents estimated coefficients (t-statistics in parentheses). The dependent variable is *Director turnover* measured by the number of directors who leave the firm in year t divided by the board size in year t-1. *VC* is equal to one if the firm receives VC investment in a given year, and zero otherwise. *Sales growth* is the first difference in sales between two successive years. *Employment growth* is calculated by the first difference in the number of employees between two successive years. Other controls include total asset, board size, firm age and director age. Heteroskedasticity-robust standard errors are clustered at firm level.* p<0.1, ** p<0.05, *** p<0.01

Table A4. Alternative firm relative performance measure

	(1)	(2)	(3)
VC	0.053***	0.049***	0.051***
	(2.99)	(2.82)	(2.85)
Median-AdjROA	-0.008*	-0.001	-0.001
	(-1.84)	(-0.34)	(-0.32)
VC* Median-AdjROA		-0.073***	-0.071***
		(-3.72)	(-3.67)
Director tenure	0.070***	0.070***	0.071***
	(9.22)	(9.26)	(9.13)
Director age	0.077	0.073	0.077
	(1.48)	(1.42)	(1.47)
Board size	0.084***	0.083***	0.083***
	(6.44)	(6.33)	(6.12)
Total assets	-0.008*	-0.009*	-0.011**
	(-1.80)	(-1.93)	(-2.30)
Firm age	-0.069***	-0.069***	-0.064***
	(-5.32)	(-5.38)	(-4.68)
Constant	-0.163	-0.135	-0.085
	(-0.78)	(-0.65)	(-0.39)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	No	No	Yes
N	9169	9169	9169
Adj. R-sq	3.33%	3.77%	4.30%

Note: This table presents estimated coefficients (t-statistics in parentheses). The dependent variable is *Director turnover* measured by the number of directors who leave the firm in year t divided by the board size in year t-1. *VC* is equal to one if the firm receives VC investment in a given year, and zero otherwise. *Median-AdjROA* is estimated by subtracting the (two-digit SIC code) industry median ROA value each year from each firm's ROA. * p<0.1, ** p<0.05, *** p<0.01.

Conclusions

This thesis explores the relationship between VCs and portfolio firms. We first focus on the biotechnology sector and delve into the moderating effects of local investment experience on distant VC investments. Findings indicate that local investment experience heightens the likelihood of financing early-stage ventures by distant VCs. However, local experience fails to positively moderate the impact of geographic distance on partnership performance, including follow-on funding and successful exits. This research underlines that although geographic distance presents challenges, VC investors can glean knowledge from local investments. Distant VCs, buoyed by local investment experience, can enhance their risk attitudes and make more informed investment decisions. Then we examine the relationship between VC diversification strategy and portfolio firms' performance. The findings suggest a positive impact of VC prior diversification on portfolio firms' performance. In contrast, current VC diversification exhibits a negative correlation with firm performance. This chapter makes a significant contribution to the VC literature, delving into the rarely examined sphere of VC influence on portfolio companies, particularly concerning diversification strategies. The implications of this study reveal that VC diversification not only aids in risk mitigation but also facilitates the accumulation of diverse expertise, which, in turn, fosters the future growth of young ventures. It becomes evident that prudent selection and strategic allocation of resources across diverse projects are essential for optimal portfolio firm performance. Importantly, VC managers must strike a balance between diversification and performance enhancement, as over-diversification could impede portfolio firm performance. This insight, particularly relevant for emerging VC firms aiming to establish a reputation for superior portfolio performance, offers valuable strategic guidance. Finally, the third chapter explores the role of VC monitoring in portfolio firms, revealing a higher turnover of directors in VC-backed companies compared to non-VC-funded counterparts. Significantly, director turnover in VC portfolio firms is more sensitive to performance and growth. Board members in VC-backed firms face pressures and incentives tied to performance outcomes. This insight empowers the board of directors in VC-funded firms to align their decisions with VC preferences, particularly during VC financial injections.

This thesis provides a comprehensive exploration of the nuanced dynamics between VC firms and portfolio companies. The insights gained offer actionable guidance for both VC firms and portfolio companies, shedding light on strategies for optimal performance enhancement, monitoring effectiveness, and navigating the challenges posed by geographic distance. These findings hold the potential to shape not only business practices but also inform policy decisions aimed at fostering vibrant entrepreneurial ecosystems and driving economic growth.

In the first chapter, the results unveiled that local investment experience enhances the likelihood of distant VC financing early-stage ventures. This finding indicates the potential for knowledge transfer across geographic boundaries, allowing distant investors to become more attuned to local dynamics and opportunities. These insights hold significance for both VC firms and portfolio companies. Policymakers can leverage these insights to encourage knowledge exchange and collaboration across regions. Initiatives that facilitate networking, mentorship, and information sharing can amplify the positive effects of local investment experience, thereby enhancing the competitiveness of regional ecosystems.

The second chapter revealed that prior VC diversification has a positive influence on portfolio firms' performance, fostering improved ROA and sales growth. In contrast, current VC diversification exhibited a trade-off with firm performance, emphasizing the need for strategic resource allocation. Policymakers and VC industry stakeholders can use these findings to encourage prudent diversification strategies among VC firms. Promoting diversified expertise and risk mitigation practices can enhance the resilience and long-term growth prospects of portfolio companies.

The third chapter focused on the relationship between VC monitoring and director turnover in portfolio firms. Our results suggest that VC-backed companies witness higher director turnover, especially in response to performance and growth indicators. These insights provide valuable guidance to board members in VC-backed firms and highlight the importance of aligning with VC goals and interests. Policymakers can recognize the importance of governance practices in VC-backed firms and encourage transparency and performance-driven decision-making. Initiatives that promote collaboration between boards and VC investors can foster an environment where performance improvement is incentivized.

This thesis advances our understanding of the dynamics within the VC ecosystem, highlighting the intricate interplay between investors and portfolio companies. The policy implications derived from these findings hold the potential to shape policy decisions aimed at nurturing thriving entrepreneurial ecosystems: facilitating cross-regional knowledge exchanges, promoting prudent diversification, and enhancing governance practises.