Cross-border VCs, Innovation, and Investment Success

by

Zicen Zhao

Submitted in accordance with the requirements for the degree of Doctor of Philosophy in Accounting and Finance

The University of Leeds
Leeds University Business School
Accounting and Finance Division
Centre of Advanced Studies in Finance (CASIF)

January 2026

Intellectual Property Statement

Acknowledgements

I would like to express my sincere gratitude to my supervisors, Prof. Shima Amini and Dr. Ali Altanlar, for their excellent mentorship, constructive feedback when I am lost and confused, and continuous encouragement when I am frustrated through my Ph.D. journey. Their insight and support have remarkably enhanced the quality of this thesis.

I am grateful to Professor Nick Wilson and Prof. Moshfique Uddin for their valuable advice on this research at my transfer stage. I would also like to thank the invaluable support from all colleagues and staff in the Centre for Advance Studies in Finance (CASIF), the department of Accounting and Finance community, and Leeds University Business School, who provides supports throughout my research.

Moreover, to my dear friends, thank you for being the best company and providing endless laugh in this tough journey. More importantly, I am truly thankful to my partner for his love, patience, and endless support throughout the difficult times of my research. Last but not the least, I would like to give my special thanks to my parents, my sister, and the whole family for their a range of supports and everlasting encouragement to my study.

Abstract

This thesis investigates three issues in the context of cross-border VC investments: how cross-border VCs impact innovation, how social connections affect cross-border VC investments, and how climate risks affect cross-border VC investments.

The first empirical chapter examines the impact of cross-border VCs on investee company innovation. This study hypothesizes that, comparing to domestic VCs, cross-border VCs exhibit less emotional attachment to their investee companies, employ distinct risk management mechanism, and leverage diverse knowledge and resources from local environment to foster innovation within investee companies. Utilizing the unique merged international VC investments and patents databases, the results suggest that there is no significant difference innovation impact between cross-border VCs and domestic VCs. Furthermore, the analysis reveals that most of the cross-border investments are from high innovation countries to low innovation countries, and then the selection process induces the bias on estimates. Therefore, this study employs Heckman two-stage analysis to mitigate the selection bias and the estimations reveal that cross-border VCs significantly increase investee company patent counts and citations. The results are robust across various measurement windows and subsamples.

The second empirical chapter investigates the role of social connections in the cause and consequences in cross-border venture capital investments. Implementing a novel proxy of Social Connectedness Index, extracted from Facebook friend connections, the results indicate that cross-border VC investors are more likely to invest in portfolio companies located in socially connected countries. However, while such social ties reduce the likelihood of successful exits, they also enable portfolio companies to access diverse resources and knowledge spillovers, enhancing their innovation performance following cross-border VC investments. Furthermore, this study employs instrument variable and Heckman two-stage model to address the potential selection bias and concerns. The findings are robust to a variety of tests and econometric approaches for dealing with endogeneity problems. The findings underscore the role of geographical structure of social

networks between countries in cross-border venture capital decisions contributing to the economic sociology and spatial economics literature.

The third empirical chapter study investigates the impact of environmental factors on VC investment behaviour and performance. Integrating climate risk indicators from multiple data sources, this study assesses the role of climate risk in shaping cross-border VC investment decisions and outcomes. The results indicate that due to salience bias, VCs from high climate risk country are more likely to invest cross-border. In addition, physical risks and transition risks reduce the likelihood of successful exits for cross-border VC investments. Moreover, stacked difference-in-differences (DiD) strategy, Heckman two-stage analysis, Cox hazard model are used to address endogeneity and ensure robust causal inference. Results are consistent and robust using alternative proxies and various tests. The findings provide new insights into the relation between climate risk and cross-border VC activity, demonstrating the importance of environmental considerations in cross-border investment strategies and outcomes.

Table of Contents

List of Tables

List of Equations

Chapter 1. Introduction

1.1 Motivation & Background

Venture capital (VC) has been serving as a vital financial intermediary by directing capital into entrepreneurial ventures from institutional investors, such as pension funds and university endowments, also knowns as limited partners. They commit capital for a fixed period of time in return for expected returns, while general partners, fund managers, are responsible for raising these funds, conducting due diligence, and selecting investment opportunities with high growth potential (Poelhekke and Wache, 2026). Beyond financing, VCs play a distinctive role in in addressing severe information asymmetries inherent in early-stage, opaque, and high-risk ventures by providing not only capital but also active monitoring, managerial expertise, and governance support (Eldar and Grennan, 2024; Bonelli, 2025; González-Uribe et al., 2026). In addition, greater geographic distance increases monitoring costs and exacerbates information asymmetries, leading VC investors to exhibit a strong home bias and historically been reviewed as primarily local investors (Cumming and Dai, 2010). However, as domestic market saturated and diminished profits in late 1990s in North America, VC investors have increasingly pursued opportunities abroad (Guler and Guillen, 2010; Harris et al., 2014). In addition, VC firms increasingly pursue opportunities across borders as entrepreneurial ecosystems globalise and as institutional and policy changes reshape cross-region investment flows. Recent evidence from European VC markets shows that regulatory and political shocks, such as Brexit, materially altered cross-region VC activity between UK and EU investment hubs, highlighting the sensitivity of cross-border VC flows to institutional change (Bosio et al., 2025).

Cross-border VC investments are often compared with international portfolio investments, as both are motivated by risk–return goals. However, Schertler and Tykvova (2011) demonstrate that portfolio investments are mainly passive, whereas VCs take an active role in monitoring their investments through rigorous due diligence, post-investment monitoring, managerial involvement, and governance support (Amit et al., 1998). Wright et al. (2005) state that such activities, intended to mitigate the information asymmetries, inherent in VC investments, but induces higher transaction and monitoring costs at the same time. The rising costs are generally greater for cross-border transactions than that for domestic ones. Therefore, cross-border VC investments are different from international portfolio investments, given such considerations.

Moreover, similarly, foreign direct investment shares some characteristics with cross-border VC investment, especially both are influential in managerial decision making in investee companies. However, different from VC investments, which primarily seek capital gains for their limited partners, foreign direct investments are typically motivated by long-term strategic objectives and sustained managerial control (Groh and Von Liechtenstein, 2009). What's more, while foreign direct investments are usually associated with majority ownership stakes, VC investors most often maintain minority positions in portfolio companies (Schertler and Tykvova, 2011). Therefore, cross-border VC investment differs fundamentally from both international portfolio investing and foreign direct investment, and a new theoretical framework is suggested by Guler and Guillén (2010). This thesis extends the growing strand of studies exploring new perspective of cross-border VC investors to understand their investments.

Previous research has investigated the patterns of cross-border VC investments. The most challenging issue for cross-border VCs is information asymmetries, so VCs seek ventures in information transparency environment, such as less institutional and cultural differences (Li et al., 2014), and local VC participation alleviates the challenges in information collecting (Nahata et al., 2014). In addition, at the country level, Nahata et al. (2014) demonstrate that stronger legal protection, enforcement, and developed capital market attract cross-border VC investments. Moreover, Guler and Guillén (2010) find that VC firms prefer host economies with advanced technological, legal, financial, and political institutions, which provide innovation opportunities, protect investor rights, and support exit channels. Both Guler and Guillén (2010) and Schertler and Tykvová (2011) emphasize the importance of innovation capacity in attracting cross-border VCs. Porter's (1990) state that differences in knowledge inputs, institutional quality, and technological capabilities create persistent national disparities. Despite globalization, these variations remain and continue to shape cross-border investment flows.

While VCs are widely recognized as key drivers of innovation (Bernstein et al., 2016), especially in the U.S. high-tech sector, existing research has primarily focused on selection criteria rather than innovation outcomes. To date, little evidence compares whether cross-border VCs contribute differently to innovation relative to domestic investors. The first empirical chapter fills this gap by employing a uniquely merged international dataset to evaluate the comparative impact of cross-border and domestic VC investments on innovation performance.

Furthermore, the second empirical chapter examine the role of social connections in cross-border VC investments. Social connections are critical in facilitating cross-border VC investments. Networks provide information on investment opportunities and resources such as hiring employees, seeking funds, finding customers, and other activities, thereby expanding the geographical scope of investments and connecting startups with cross-border investors (Sorenson and Stuart, 2001; Gompers et al., 2020). In addition, syndication and access to local networks further help reduce information asymmetries (Nahata et al., 2014). However, empirical research on this topic remains limited due to the difficulty of measuring social connections and the lack of comprehensive data. To fill in this gap, the second empirical chapter employs Social Connectedness Index, driven by Bailey et al. (2018a) from Facebook's connections data, to capture cross-country social connections and examine their influence on cross-border VC activity. This index proxies the relative intensity of connections between country pairs on the global social networks.

Besides social connections, this thesis proceeds to explore the relation between climate risks and cross-border investments in Chapter 5. With the growing recognition of climate change and its consequences, investors are updating their beliefs and reshaping their investment decisions such as capital allocations and corporate governance. For example, investors with stronger ESG commitment hold more ESG assets (Giglio et al., 2025); institutional investors influenced by communities valuing environmental and social issues enhance investee companies CSR activities (Dyck et al., 2019); and rising demand for climate-related disclosures results in greater transparency and encourages firms to reduce future carbon emissions (Cohen et al., 2023).

Moreover, investor beliefs change significantly especially following exposure to extreme weather events such as heatwaves, hurricanes, and wildfires. Choi et al. (2020) reveal that retail investors reduce holdings in carbon-intensive firms during abnormal warm weather. Fund managers become more supportive of corporate environmental initatives after exposed to high temperatures or pollutions (Di Giuli et al., 2024; Foroughi, et al., 2024). Aligned with this, Pankratz and Schiller (2024) find evidence that customers switch from suppliers hit by heatwaves to those with lower climate risks. However, little is known about whether cross-border adjust their investment strategies to climate risks. The third empirical chapter contributes to the nascent literature on how cross-border VC investors adapt their strategies in response to climate risks.

1.2 Research Question and Contributions

This thesis examines the influence of cross-border VCs on innovation and investment success. Guided by the motivations outlined above, the study focuses on three central questions: i) In what ways do cross-border VCs differ from domestic VCs, especially in the impact on investee company innovation? ii) How do social connections affect cross-border VC investments selections, innovation performance, and investment success? iii) How do cross-border VCs incorporate climate risk into their investment strategies? In addressing these questions, the thesis advances the literature by offering both theoretical insights and empirical evidence with the sample of VC investments since 1996.

Chapter 3 uses VC investment data from 1996 to 2015 and tracks outcomes through 2021, producing a sample of 10,844 observations. A subsample of investee firms with positive patent counts contains 1,562 observations. Chapter 4 uses two samples. For deal formation, I construct potential VC–portfolio company dyads by randomly pairing each VC that invested in 2019 with a portfolio company it did not fund, generating 3,265,037 possible pairs. After excluding observations with unavailable SCI data, the final sample contains 2,578,898 observations. For investment performance, I use realised deals from 1996 to 2017 and track outcomes through 2021. Restricting the analysis to cross-border VC deals and excluding observations with missing SCI values yields a final sample of 19,377 observations. Chapter 5 examines climate risk using all VC investments from 1996 to 2021 and tracks outcomes through 2025, resulting in 240,651 observations. I restrict the investment performance analysis to cross-border VC deals reduces the sample to 41,917 observations.

1.2.1 Chapter 3: Cross-border VCs and Innovation

To address the first research question, Chapter 3 investigates the number of patents the investee companies have applied and finally granted, and the number of citations of the newly granted patents, measuring the innovation quantity and innovation quality, respectively. This study, firstly, conducts the OLS regression with VC ownership and innovation outcomes. However, the results do not indicate a significant difference between cross-border VCs and domestic VCs. Furthermore, following the study Tian (2012), I conjecture the selection process induce the bias on estimates. The results indicate that cross-border VCs are more likely to invest high innovation potential investee companies, which are far from achieving innovation outputs and it takes years for investee company to grow before having a patent. Therefore, this study follows Tian (2012) employ Heckman two stage method to mitigate the selection bias. As a result, the results show that cross-border VCs significantly increase investee company patents counts and citations, especially when they invest from high innovation country to low innovation country. The results remain robust across various tests, measurement windows, and subsamples.

This study extends the literature on VC's role in value creation (Gorman and Sahlman, 1989; Barry et al., 1990; Sapienza, 1992; Tian, 2012; Ma, 2020; Gompers et al., 2020; Conti and Graham, 2020; Shin et al., 2025). In particular, this chapter directly contributes to how VC investments increase innovation. Prior research has largely focused on domestic VC firms (Popov and Roosenboom, 2012; Tian, 2012; Chemmanur et al., 2014; Tian and Wang, 2014; Bernstein et al., 2016; González-Uribe, 2020; Lerner and Nanda, 2020; Matray, 2021; Chemmanur et al., 2022) or on foreign investors and cross-border M&A (Lerner, 2011; Luong et al., 2017; Bena et al., 2017; Bohn et al., 2020; Hsu et al., 2021). However, this chapter investigates the distinctive role of cross-border VCs in fostering innovation, highlighting their impact on both the quantity and quality of innovation outcomes.

This research also contributes to literature on cross-border VCs. While the existing studies have examined how cross-border VCs differ from domestic VCs (Li et al., 2014; Espenlaub et al., 2015; Nahata et al., 2015; Buchner, et al. 2018; Plagmann and Lutz, 2019; Chemmanur et al., 2020; Wang, 2020), and how they leverage resources through active monitoring (Barry et al., 1990; Bottazzi et al, 2008; Bernstein et al, 2016), reputation (Nahata, 2008), manager network (Hochberg et al., 2007), and syndication (Khurshed et al., 2020), most work focuses on investment performance. This relation between cross-border VC investors and investee company innovation remains underexplored. This study addresses this gap by analysing the impact of cross border VC on investee company innovation.

1.2.2 Chapter 4: Social connections and Cross-border VCs

To investigate the second research question, Chapter 4 tests the role of social connectedness in cross-border VC investments selection, financial performance, and innovation performance. First, this study conducts a counterfactual analysis on 2,587,898 potential VC-PC pairs to assess the likelihood of cross-border VC investment, utilizing logit and probit regression models. The findings indicate that cross-border VC firms are more likely to invest in portfolio companies located in countries with strong social ties. Furthermore, this study examines the performance of cross-border venture capital investments, focusing on both financial and innovation outcomes. The results reveal a negative correlation between social connectedness and the likelihood of successful exits, showing that while social connections facilitate investment, they do not necessarily translate into higher success rates for exits. More importantly, this study extends the analysis to the innovation performance of portfolio companies. This research applys the Poisson pseudo-maximum likelihood estimator to evaluate the impact of social connectedness on the number of patents and citations. The results demonstrate that, despite the lower success rate in financial exits, portfolio companies backed by socially connected VC investors tend to produce significantly more patents and receive more citations, reflecting enhanced innovation performance. Moreover, this study implements two methods to address potential concerns: using instrumental variables, internet user coverage in VC country, to control for endogeneity and employing the Heckman two-stage regression to correct the selection bias. The results are consistent with previous baseline estimates, indicating a significant negative relationship of social connectedness on success exits. Taken together, the results support the hypotheses that cross-border VC investors are more likely to invest in portfolio companies within socially connected countries. Nevertheless, these close social relations adversely affect portfolio company performance, decreasing the likelihood of successful exits. Conversely, portfolio companies leverage diverse resources and knowledge spillovers by cross-border VCs, improving their innovation performance after cross-border VC investments.

This chapter contributes to three strands of literature. First, it extends economic sociology by examining the role of social connectedness in economic outcomes. Existing research shows social connectedness determinates financial decisions, such as stock selection (Cohen et al., 2008), housing purchases (Bailey et al., 2018b). In addition, social connectedness also influences capital market (Ertug et al., 2022; Hirshleifer et al., 2024) and investment choices in mergers and acquisitions (Cai and Sevilir, 2012) as well as in the crowdfunding market (Peng and Zhang, 2024). In VC industry, however, research has primarily concentrated on interfirm and networks (Sorenson and Stuart, 2001; Gompers et al., 2016; Nguyen et al., 2023), with limited attention to general regional or cross-country connectedness. This research advances the literature by investigating the intercountry social connectedness in cross-border VC investments and, importantly, by analysing these investments not only to financial outcomes but also to subsequent innovation performance.

Second, this study further contributes to spatial economics by examining how geographic distance shapes cross-border VC investments decisions. Prior research has investigated about the influence of geographic distance in domestic deal selection and portfolio company value creation (Chen et al., 2010; Cumming and Dai, 2010; Zaheer and Mosakowski, 1997; Li et al., 2014; Nahata et al., 2014; Dai and Nahata, 2016) and how VCs address liability of foreignness and derive benefits from such investments (Tian, 2011; Espenlaub et al., 2015; Bernstein et al., 2016; Buchner et al., 2018; Khurshed et al., 2020). However, few studies investigate the causes of cross-border VC investments and how VCs select investment opportunities in the context of geographical distant countries. This research aims to fill this gap by examining the deal formations and extending the analysis to evaluate investment outcomes in both finance and innovation.

Third, this study contributes to the literature on corporate innovation by examining cross-border VC investments in the context of social connectedness. Prior research highlights determinates of innovation such as board composition (Chen et al., 2018; An et al., 2021); CEO traits (Hirshleifer et al., 2012; Bernile et al., 2017; He and Hirshleifer, 2022), managerial quality (Chemmanur et al., 2019), and tolerance of early failures while rewarding long-term success (Manso, 2011). However, most VC studies remain focused on domestic settings (Chemmanur et al., 2014; Tian and Wang, 2014; Ewens and Marx, 2018), largely due to data limitations. Using the Orbis-IP international patent database, this research extends the literature by analyzing how cross-border VCs influence innovation through inter-country social connectedness. Relying on the Social Connectedness Index (SCI; Bailey et al., 2018a) and patent citations, the study shows that social ties facilitate knowledge diffusion and shape innovation outcomes. To my knowledge, this is the first study to quantify inter-country connections between VC firms and portfolio companies and evaluate their effects on innovation performance.

1.2.3 Chapter 5: Climate risks and Cross-border VCs

Chapter 5 answers the third research question. The primary measure of physical climate risk used in this study is the Global Climate Risk Index (CRI) from Germanwatch (Eckstein et al., 2021), which quantifies country-level economic losses from extreme weather. In addition, this study incorporates the Notre Dame Global Adaptation Initiative (ND-GAIN) indices covering both physical risks and transition risks. This study examines the role of climate risk in cross-border VC investments selection and financial performance. The research begins with estimating how home-country climate risk affects the VC firm invests internationally. The results from probit regression reveal that higher home-country climate risk significantly increases the likelihood of cross-border VC deployment. Furthermore, this study examines the influence of physical risks and transition risks on cross-border investments exits performance. I conduct probit regression of successful exits on physical risks and transition risks, and discover that physical risks reduce successful exits rates, while readiness capacity promotes successful exits, which also indicates a lower transition risk.

To further validate these results, this study conducts more robustness tests and alternative measurements in further tests, including stacked difference-in-differences (DiD) identification to mitigate endogeneity issues, such as other factors influence investment decisions. In addition, this study utilizes instrument variable, population density for climate risk, and Heckman two-stage procedure to mitigate selection bias in investments. The results are consistent with previous findings, indicating transition risks are more salient and significant to investments performance. Furthermore, this study applies cox hazard model to examine the determinates of VC successful exits, especially how climate-related physical risks affect investment outcomes and finds consistent results that higher physical risk reduces the likelihood of successful exits and delay the exits time. In addition, this research uses alternative proxies for climate risk, *CRI Rank*, and lagged climate risk indicators, and the results are consistent with the primary results, and confirming the robustness of the findings.

This study contributes to the general literature on climate finance, especially investor response about climate risk. Although the growing body of evidence on how climate risks influence firms and financial market participants decisions (Huang et al., 2018; Krueger et al., 2020; Stroebel and Wergler, 2021; Ilhan et al., 2021; Ginglinger and Moreau, 2023), a few research studying about how VC investors react to climate risks. Huang et al. (2024) find that reduced VC investments in natural disaster zones in US. However, whether cross-border VCs react on their international portfolio allocations concerning about climate risks is still unknown. This study aims to fill this gap by assessing both the likelihood of cross-border VC investments and the subsequent investments performance outcomes.

This research also contributes to the cross-country research examining climate-related behaviours. For example, high governance institutions enhance firms' CSR performance (Cai et al., 2016), and low uncertainty avoidance encourages VC cleantech investments (Cumming et al., 2016). This study advances prior research by examining how home-country climate risks reshape cross-border VC investments allocations and investments performance. Overall, this study integrates insights from institutional, cultural, and policy literatures to offer the first comprehensive analysis of climate risk's role in cross-border VC dynamics and its implications for sustainable entrepreneurship.

1.3 Structure

This thesis includes seven chapters. The remainder of the thesis is organised as follows. Chapter 2 illustrate the literature review of the role of VC and cross-border VC development. Chapter 3 examines cross-border VC investors' impact on innovation. Chapter 4 investigates the role of social connectedness in cross-border VC investments decisions and impact. Chapter 5 presents an analysis of the relation between climate risks and cross-border VC investment selections and outcomes. Chapter 3 to Chapter 5 have their own introduction, literature review, hypothesis development, data and sample selection, empirical results, and conclusion. Chapter 6 concludes the thesis, offers some policy implications, and identifies areas for ongoing and future research. Finally, Chapter 7 displays the references.

Chapter 2: Literature Review

2.1 Venture Capital

Venture capital firms raise funds from limited partners, such as pension funds and university endowments, invest funds into venture capital firms, and then the general partners, also known as the fund managers, conduct due diligence, screening, and eventually select high growing potential investment opportunities and targets to invest capital in (Ewens and Farre-Mensa, 2022; Shin et al., 2025). There is growing literature about the role of venture capital in investments, especially how venture capital adds value to investee firms. Besides providing financial supplies to investee companies, venture capitals also perform some non-financial services and guidance to create company value, including screening and deal selection, contracting, monitoring, advising, and coaching (Li et al., 2014).

Firstly, VCs increase investee company value through screening and deal selection. VCs are expert at identifying future potential ventures (Baum and Silverman, 2004). The value-adding decisions are made by investment managers with professional selection skills identify and evaluate the investment opportunities and potential projects (Manigart and Wright, 2013). Furthermore, some studies reveal the decision-making process and decompose the VCs assessments. Shepherd (1999) finds that VCs assess new venture survival mainly by the level of uncertainty and the ability of the management team to cope with the external environment changes. Baum and Silverman (2004) illustrate that VCs finance start-ups with strong technology background. In addition, a good management team also signals a potential investment opportunity for VCs. Wright and Robbie (1998) and Muzyka et al. (1996) indicate that VCs select the opportunity which offers a good management team and reasonable financial and product characteristics. Gompers et al. (2020) argue that VCs prioritize the management and founding team in deal selection, especially among early-stage and information technology investors.

Secondly, contracting is the ongoing process of negotiating and renegotiating contracts to protect the right of investors to adapt the uncertainty and information asymmetries between principals and agents (Sahlman, 1990; Li et al., 2014). Admati and Pfeiderer (1994) study the role of VC in contracting and suggest that as the insider investors, VCs consistently make optimal investment with a fixed-fraction contract, leading to a consistent predetermined fraction of the project's payoff for VCs and at the same time, the same fraction to future investments. Moreover, the fixed-fraction contract discourages VCs to misprice the securities issued during the following rounds. In addition, contracting is a way to staging the commitment of capital and preserve the option to stop investments. Practical contracts design the compensation mechanism to enhance investee company value creation and performance (Sahlman, 1990). Furthermore, Cong and Xiao (2022) discover that when VC investors cooperate various funds, they employ contingent payments and tiered contracts to promote project nurturing and managerial enhancement. Successful funds are rewarded with continuation contracts that exhibit tolerance failure and incentivize innovation. In the line of the optimal split between agents and maximizing the probability of success, Ewens et al. (2022) find that contracts materially affect the value of the firm and the split between ventures and investors. Although VCs utilize their bargaining power to process more investor-friendly terms compared to the contract that maximized investee company values, having a higher quality VC still benefits the investee companies and increase their values.

Prior studies have long established that venture capitalists provide value beyond financing through active monitoring, governance, and strategic support. Recent evidence further confirms this value-added role by showing that VC involvement can shape portfolio company development through due diligence, board participation, investor networks, and portfolio-level resource sharing. For example, Eldar and Grennan (2024) show that common VC investors and shared directors across same-industry startups can increase subsequent financing, reduce failure, and improve exit outcomes, suggesting that VC investors create value through governance and network-based coordination. Similarly, González-Uribe et al. (2026) show that VC due diligence affects startup development even for firms that do not ultimately receive funding, indicating that the VC evaluation process itself may generate learning, strategic refinement, and capability-building effects for entrepreneurial ventures.

VCs also contribute to investee companies through advising and coaching services. VCs help investee companies identify and strengthen its comparative advantage and development strategy. Sapienza et al. (1996) suggest that VCs provide oversight and deeply involved of portfolio companies, adding value beyond the money they provide to the portfolio companies. To be more specific, the VCs' professionalization and coaching services include providing market strategy to investee companies, which brings product to market faster (Hellmann and Puri, 2000), recruitment of the management team, and professionalizing business model to assist founders (Hellmann and Puri, 2002; Kaplan and Stromberg, 2004), and administrative support, certifications, attracting professional managers, and increasing workforce size (Li et al., 2014). This suggests that investor value creation depends not only on capital provision but also on the match between investor resources and venture needs.

A growing strand of recent research also examines how specific VC characteristics shape value creation. Eldar and Grennan (2024) show that common VC ownership can generate benefits for startups through shared governance and investor networks. Tian (2012) specifies the role of venture capital syndication in value creation. This study suggests that VC syndication creates product market value and financial market value for portfolio firms. Additionally, VC syndicate-backed firms are more likely to exit successfully, have better financial market performance, shown as a lower IPO underpricing, and have higher IPO market valuation. Moreover, Ma (2020) focusing on corporate venture capital (CVC), studies the entry, investment, and termination of CVC investments from an innovation perspective, and investigates the role of CVC in firm innovations.

However, identifying and monitoring the most promising early-stage startups is challenging for VCs without sufficient information transparency and geographic distance (Howell, 2020). Cumming and Dai (2010) suggest that VCs are more likely to invest in geographically proximate companies to reduce costs and increase involvements and monitoring. Lerner (1995) also indicates that venture capitalists are less likely to serve on board in distant companies. However, Han et al. (2025) show that COVID-19 lockdowns increased VC investment in more distant startups, with stronger effects where internet infrastructure was better and information asymmetry was lower. This suggests that digital connectivity can partially weaken the traditional locality of VC investment, but distance-related information and monitoring costs remain central to investment decisions. Therefore, this thesis is built on these studies to investigate how cross-border VCs incorporate distance and investment success.

2.2 Cross-border Venture Capital

2.2.1 Development

In recent years, there has been a noteworthy upward trend in venture capital investments across national borders, as venture capitalists actively pursue investment opportunities beyond their home country (Weik, 2024; Nguyen et al., 2025). Information about potential investment opportunities spread in VC industry and across boundaries, thereby expanding the spatial investment radius of VC investors (Sorenson and Stuart, 2001; Devigne et al., 2016; Akcigit et al., 2024). Bruton et al. (2006) propose that build on US VC modes, VCs organize and behave around the world, spreading to Europe, Asia, and next to Latin America, Africa, Middle East. International VC is becoming increasingly significant, both in terms of the substantial financial investments and its expanding geographic diversity (Wright et al., 2005; Boryniec et al., 2023).

2.2.2 Motivation

Previous literatures suggest that international venture capital investments have been driven by the three factors. First, VC firms and VC industry markets are developing internationally. VC firms are originated from US, and then spread to the UK and western Europe and to Japan (Ooghe et al., 1991; Wright et al., 2005). Meanwhile, the VC industry market is growing globally. Numerous developing countries have undertaken radical regulatory reforms, rendering them more appealing for potential investors (Gompers and Lerner, 1998). Noteworthily, the VC markets in Singapore has become well established and markets in other Asian countries are growing rapidly especially in India and China (Kenney et al., 2002; Wright et al., 2005).

Second, domestic markets are saturated, so VCs are seeking new opportunities in other countries to overcome the shortages of domestic investments as well as diversify portfolio (Wright and Robbie, 1998; Buchner et al., 2018). When high levels of VC funds oversupply the limited investment opportunities in domestic markets, VCs choose to enter a new market abroad (Buchner et al., 2018) to protect its returns. In addition, considering portfolio diversification, VCs make the decisions to invest cross-border, especially for the investors whose portfolios are primarily allocated in domestic ventures (Poterba and French, 1991). VC firms aim to benefit from cross-border investing by achieving portfolio diversification and overcoming shortages of domestic investment opportunities in saturated markets (Buchner et al., 2018).

Third, high growth potential and developing new markets abroad are attractive to VC investors, comparing to their developed domestic market (Baygan and Freudenberg, 2000; Guler and Guillen, 2010). Wright et al. (1992) and Murray (1995) find that UK VCs enter new cross-border markets when opportunities decline in their original market, leveraging their expertise as a competitive advantage. They then capitalize on emerging opportunities through cross-border investments. Furthermore, Dai et al. (2012) and Weik (2024) indicate that VCs select high innovative and high growth potential portfolio companies in the foreign markets and then commercialize the opportunities to earn returns.

Furthermore, recent studies show that VC activity has become increasingly international. Shi et al. (2024) document the international migration of venture-backed startups and show that startups are more likely to relocate to places with stronger VC availability, particularly when their investors have connections in those locations. Bosio et al. (2025) further show that Brexit reshaped cross-region VC flows between the UK and EU, highlighting how institutional and political changes can materially affect cross-border VC activity.

Taken together, these studies provide a recent foundation for examining how cross-border VCs incorporate geographic, institutional, and relational distance into investment decisions.

2.2.3 Liability of Foreignness and Decision Making

Due to the liabilities of foreignness, cross-border VCs employ distinct investment strategies compared to domestic VCs, reflecting differences in selection and monitoring approaches**.** Wright et al. (2005) highlight cross-border venture capitalists exhibit some distinctive characteristics on investing and decisions making. Therefore, this section reviews the literatures to understand how cross-border VCs act differently from general VCs and domestic VCs. Particularly, from the macro level, VC international industry development and market conditions, and the micro level, VC investor behaviours.

On the macro level of cross-border VC investments, challenges stemming from geographical, cultural, and institutional disparities between the home and host countries contribute to significant liability of foreignness faced by cross-border VCs in international investment (Zaheer, 1995; Meyer and Shao 1995; Nahata et al., 2015; Buchner et al., 2018; Liu and Maula, 2021). Dai et al. (2012) highlight that foreign VCs are more likely to invest in ventures with high information transparency, particularly when investing alone. In specific, previous research indicate that institutional and cultural distances decrease VCs' effectiveness in conducting venture capital activities and generate higher transaction cost and greater costs due to more severe information asymmetries and agency conflicts. So institutional and cultural distances negatively affect investment performance in terms of exit success and rate of return (Wright and Robbie, 1998; Portes and Rey, 2005; Li et al., 2014; Buchner et al., 2018). Moreover, Nahata et al. (2015) highlight that investee countries boasting more developed stock markets tend to exhibit improved performance. Furthermore, the existence of superior legal rights and enforcement within the investee country is positively associated with the success of cross-border VC investments, while cultural distance plays a constructive role in enhancing VC success through rigorous screening and selection of investments. Consistent with this, Espenlaub et al. (2015), and Cumming et al. (2016) find that cross-border VCs exit faster in highly liquid markets, favouring IPO exits with higher proceeds.

On the micro level, Although VC investors display local bias in investments (Cumming and Dai, 2010; Devigne et al., 2016; Wu and Salomon, 2017), certain VC characteristics and strategies reduce such bias and expand VC investments scope. Cumming and Dai (2010) state that VC reputation mitigates the local bias, and more reputable VCs are associated with less local bias in their decision making. Additionally, Wu and Salomon (2017) find that foreign firms equipped with superior human capital capabilities and local experience are better equipped to navigate regulatory challenges effectively. Furthermore, Sorenson and Stuart (2001) show that investment experience extends the geographic scope of investments, and some VC investors show less local bias, especially larger VC investors.

Moreover, VC employ distinct investments strategies to mitigate information asymmetry issues and liability of foreignness. For example, VC investors monitor distant companies through stage financing, enabling them to abandon underperformed projects, shown as more financing rounds, shorter intervals between rounds, and smaller investments per round (Tian, 2011). In addition, local VC participations are valuable for cross-border investments. Humphery-Jenner and Suchard (2013) reveal that foreign investors can boost the cross-border investments success by adding joint ventures, especially who are domestics. Local VC partnership alleviate information asymmetry and liability of foreignness, and local VC involvement facilitates cross-border VC investor monitor ventures more effectively. Consequently, portfolio companies, especially as they expand internationally, benefit from cross-border engagement (Guler and Guillen, 2010; Devigne et al., 2013; Weik, 2024).

Chapter 3: Cross-border VCs and Innovation

Abstract

This study examines the impact of cross-border VCs on investee company innovation. By contrasting cross-border VCs with domestic VCs, I hypothesize that the cross-border VCs are less emotional attached to investee companies, employ distinct risk management mechanism, and leverage diverse knowledge and resources from local environment to foster innovation within investee companies. Utilizing the unique merged international VC investments and patents databases, I didn’t find significant difference innovation impact between cross-border VCs and domestic VCs. Furthermore, the results indicate that most of the cross-border investments are from high innovation countries to low innovation countries, and then the selection process induces the bias on estimates. Therefore, this study employs Instrument variable and Heckman two-stage analysis to mitigate the selection bias. The analysis reveals that cross-border VCs significantly increase investee company patent counts and citations. The results are robust across various measurement windows and subsamples.

3.1. Introduction

Innovation is fundamental for economic growth and determines a country’s long-term economic growth and competitive advantages (Solow,1957). Similarly, for a firm, innovation is vital for its value and long-term success (Bulter, 1988; Porter, 1992; Babina et al., 2024). However, innovations are very difficult, along with high risks. Investment in research and development (R&D) is capita and time-consuming (Hou et al., 2021) and Holmstrom (1989) argues that “innovation is intrinsically risky and progress more erratic than with standard investments”. Venture capital is known for providing financial support as well as monitoring service for investee firms further growing. Carrying experience and resources, venture capitals actively monitor investee firms, add values, motivate and nurture innovation at the same time. Considering costs and the inherent risks of innovation, it is interesting to investigate how VC funds simulate innovation by backing the ventures (Chemmanur et al., 2014). Furthermore, with the development of globalization, venture capital investments are not limited domestically, but also expanding cross-border to the whole world (Weik, 2023). Recently, cross-border venture capital investments are growing rapidly as evident by increasing deals and expanding capital size. According to the CB Insights report in "State of Venture", venture capital investments have been more than doubled in 2021, reaching $621 billion globally, which is higher than the previous year's record of $294 billion (CB Insights, 2022[1]).

However, cross-border VC investments are different from domestic VC investments in many aspects. In general, geographic distance is the main difference between cross-border VCs and domestic VCs, which induces other distances, such as cultural distance and institutional distance (Zaheer, 1995; Meyer and Shao 1995; Li et al., 2014; Nahata et al., 2015; Buchner et al., 2018; Poelhekke and Wache, 2026), which make further impact on investee firm innovation. In this study, I am interested to investigate whether cross-border VCs will have a greater impact on investee company innovation. I make the hypothesis based on three features of cross-border VCs.

Firstly, cross-border VCs are detached from the local economic environment and less emotional attachment with investee companies, so I conjecture less emotional attachment is associated with less social pressure and more effective engagement and commitment to investee companies. In addition, cross-border VCs monitor investee companies externally and rationally, reducing the agency problems, and supporting the investee companies growing and more innovations. Secondly, cross-border VCs conduct their own distinct risk management mechanism in investments to overcome the challenges driven by geographic distance. Additionally, cross-border investments are made for different purpose from domestic investments. Bena et al., (2017) suggest that regardless of the investment performance, most cross-border VC investments are aimed to diversify risks by investing cross-border. I expect the differences investment motivation, in consequence, leads to cross-border VCs are more tolerant for investments and increase investee company innovation. Thirdly, cross-border VCs diffuse knowledge at the firm and country levels and then provide different supports and value-adding services to entrepreneurs. On the firm level, I speculate cross-border VCs have the capability to engage with investee firms to ascertain their

[1] CB Insights (2022). State of Venture 2021 Report, (https://www.cbinsights.com/research/report/venture-trends-2021/) Accessed May 1, 2022.

fundamental strengths and facilitate to develop innovation efficient. Furthermore, I also expect cross-border VCs diffuse knowledge and innovation between firms and spur innovation. On the country level, I argue that the cross-border VC investments from high innovation country spill over the knowledge to investee companies and enhance their innovation. To summarize, with the increasing trend of cross-border venture capital investments and considering the differentiate features of cross-border VCs, this study aims to cast light on the role of cross-border VCs for investee companies, especially on investee firm innovation.

To test the role of cross-border VCs in investee company innovation, I start with venture capital investments data from Eikon, from 1996 to 2015. Furthermore, I track the VC investments outcomes in 3 years and 5 years. Specifically, I investigate the number of patents the investee companies have applied and finally granted, and the number of citations of the newly granted patents, measuring the innovation quantity and innovation quality, respectively. In this study, firstly, I conduct the OLS regression with VC ownership and innovation outcomes. However, the results do not indicate a significant difference between cross-border VCs and domestic VCs. Furthermore, following the study Tian (2012), I conjecture the selection process induce the bias on estimates. The results indicate that cross-border VCs are more likely to invest high innovation potential investee companies, which are far from achieving innovation outputs and it takes years for investee company to grow before having a patent. Therefore, this study follows Tian (2012) employ Heckman two stage method to mitigate the selection bias. As a result, I find that cross-border VCs significantly increase investee company innovation, especially when they invest from high innovation country to low innovation country.

This study makes several important contributions to the literature as follows. First, it adds to the literature on the role of VC in value creation for investee firms (Gorman and Sahlman, 1989; Barry et al., 1990; Sapienza, 1992; Tian, 2012; Ma, 2020; Akcigit et al., 2024). In particular, this work directly contributes to how VC investments increase innovation. The existing literature mainly focuses on domestic VC firms (González-Uribe, 2020; Bernstein et al., 2016; Chemmanur et al., 2014; Tian and Wang, 2014; Popov and Roosenboom, 2012; Tian, 2012). There is little evidence on the role of cross-border VC investors in innovation (Lerner, 2011; Luong et al., 2017; Bena et al., 2017). This study advances this literature by studying the role of cross-border VC firms in enabling and improving investee firms' innovation in both quantity and quality.

Second, this study adds to the literature on the role of cross-border VCs. As VCs expand their investments pool internationally, more studies about how cross-border VCs are different from domestic VCs (Li et al., 2014; Espenlaub et al., 2015; Nahata et al., 2015; Buchner, et al. 2018; Plagmann and Lutz, 2019; Chemmanur et al., 2020; Wang, 2020) are emerging. There are also studies which explore how cross-border VCs utilize their diverse resources to provide value-adding services to entrepreneurs, such as through active monitoring (Barry et al., 1990; Bottazzi et al, 2008; Bernstein et al, 2016), reputation (Nahata, 2008), manager network (Hochberg et al., 2007), and syndication (Khurshed et al., 2020). The extant literature mostly focus on the performance of cross-border VC investments, while the relation between cross-border VC investments and entrepreneurial firms' innovation is not extensively explored. This study, therefore, fills this gap, by exploring the impact of cross border VC on investee company innovation.

Third, this study contributes to the literature investigating the determinants of innovations (e.g. Popov and Roosenboom, 2012). However, most previous studies, on the relationship between VC investment and innovation, focus on domestic VC (Tian and Wang, 2014; Chemmanur et al., 2014). Considering the differences between domestic VC and cross-border VC, I seek to this relationship for cross border VC investments and to investigate the determinants of innovation as well as interactions between the determinants and uniqueness of cross-border VC. In this vein, this study, also, contributes to Bena et al. (2017) and Luong et al. (2017) which acknowledge the difference between foreign institutional investors and domestic institutional investors and show that foreign institutional investments significantly increase corporate innovation (Bena et al., 2017; Luong et al., 2017).

Finally, this study complements the study by Chahine, Goergen, and Saade (2022) that examines foreign VC firms enhance investee's innovation. Using U.S. IPOs data from 2000 to 2010, they identify the beneficial effects of foreign VC firms, especially CVC firms, access to the research generated by the research department of their organization, and then increase innovation. Their work is an important and interesting attempt to understand foreign VC roles. This study differs from theirs in three aspects. First of all, this study specifies the role of cross-border VCs in innovation and bring new perspectives on how cross-border VCs increase innovation. I identify cross-border VCs as the external monitors, which leads to less emotional attachments and more effective active monitoring; cross-border VCs are more tolerant of failure; cross-border VCs spill over their knowledge to investee firms; furthermore, I test other VC characteristics and deal characteristics that influence innovation. Secondly, this work is supported by a larger and more diverse dataset by covering worldwide private and public firms over a longer period. Besides U.S. firms, I include emerging economies as well in the main sample, which test hypotheses in a broad world setting. In addition, the sample involves not only public firms but also private firms, which covers more information about the investee firms, especially some pre-matured firms, for which capital is vital for further development. The broad data set allows me to provide evidence on the determinants of innovation increase in both developed and emerging economies and examine various aspects of the deal-specific information, including industry characteristics and venture capital characteristics. Thirdly, besides the quantity of the innovation, this study also examines the quality of the innovation by the number of patents citations, which enables us to quantify the impact of their patents and innovation. Therefore, this study complements their paper and further clarifies how cross-border VCs improve investee firms' innovation.

The rest of this chapter is organized as follows. Section 2 discusses the literature review and testable hypotheses development. Section 3 demonstrates the data and sample selection. Section 4 presents variable definition and construction. Section 5 displays summary statistics. Section 6 illustrates the empirical tests and methodology. Section 7 exhibits robustness tests. Section 8 displays the conclusion. Finally, Section 9 presents the Appendix, including variable definitions, and table results.

3.2. Literature Review and Hypothesis Development

In this part, I review the literature on the determinants of innovation and illustrate the hypothesis development.

3.2.1 Literature Review - Innovation

Innovation is widely recognized as the key driver for the firm's long-term comparative advantage and economic growth (Solow, 1957; Aghion and Howitt, 1992; Gompers, 2002; Popov and Roosenboom, 2012; Babina et al., 2024). The existing literature investigates the determinants of innovations. For example, it is documented that social trust spurs innovation and promote economic productivity (Kondo et al.,2020); CEO trust level increases corporate innovation (Kong et al., 2021); countries with entrepreneurship-friendly environment benefits innovation, such as lower taxes on capital gains (Popov and Roosenboom ,2012); tolerance for failure is positively related to corporate innovation (Tian and Wang, 2014). Furthermore, investors play a vital role catalysing investee company innovation. Kortum and Lerner (2000) and Hellmann and Puri (2000) examine that VCs inspire more innovation and are associated with a significant higher patenting rate. In addition, VC syndication and CVC brings more resources for investee companies, and increase innovation (Tian, 2012; Chemmanur et al., 2014; Zhang, 2025). Moreover, some research prove that foreign investors increase innovation, specifically, foreign institutional ownership has a positive causal effect on firm innovation by active monitoring, insurance for managers against innovation failures, and knowledge-spillover (Bena et al., 2017; Luong et al., 2017; Akcigit et al., 2024). However, the detailed relationship between cross-border VCs and innovation has not been fully explored yet. In this study, I aim to fill this gap by investigating the relationship between cross-border VCs and innovation. In particular, using data on both private and public firms receiving VC investment across 116 countries, this study contributes to the existing literature by exploring whether cross-border VCs will have a greater impact on the quality and quantity of innovation compared to domestic VCs.

3.2.2 Hypothesis Development

This study is motivated by the study of Luong et al. (2017) on the relationship between foreign institutional investors and innovation. Using the public firm data from 26 non-U.S. economics between 2000 and 2010, Luong et al. (2017) propose that foreign institutional investors enhance investee firm innovation and identify three mechanisms of how foreign institutional investors increase innovation, which is monitoring, insurance, and knowledge spillover. I argue that similar to foreign institutional investors, cross-border venture capitalists share some common characteristics with foreign institutional investors, such as investing from a different country and in risky projects. Therefore, I hypothesize cross-border VCs have a greater impact on innovation than domestic VCs, based on three aspects, which are less emotional attachment, distinct risk management mechanism, and knowledge diffusion.

i. Less Emotional Attachment

Firstly, investing cross border and facing challenges from geographic distance, VCs are detached from the investee firms' local environment and have less attachments to the investee firms, physically and emotionally. Hence, I argue, with less emotional attachments to investee firms, cross-border VCs demonstrate sustained engagement and commitment to investee companies, and monitor investee companies externally, making rational decisions, eventually increasing innovation.

I infer that cross-border VCs maintain sustained engagement and commitment to investee companies from two aspects. Frist of all, domestic VC firms have frequent social interactions with entrepreneurs, and then more emotional attachments are created between domestic investors and entrepreneurs (Devigne et al., 2016). Without the emotional bonding, cross-border VCs conduct formal procedure to build connection and attachment with their portfolio companies. To be more specific, cross-border VCs adopt a more transactional approach, using high-powered contracts with well-defined and strict benchmarks (Dai et al., 2012) and staging. Tian (2011) suggests that VCs, located far away from the entrepreneurial companies, invest in large number of rounds and shorter durations between rounds, with a small number in each round. As a result, the staging positively boost the investee company development. Hence, I conjecture that cross-border VCs exhibit less emotional attachment to investee companies. They implement an elaborated monitoring system facilitated by contracts and benchmarks, ensuring sustained engagement and commitment to investee companies. Another positive effect from with less emotional attachment between cross-border investors and investee companies is less connection with the local environment and business, as well as less social pressure to make decisions. Devigne et al. (2016) assert that emotional attachment and social pressure have a greater impact on domestic firms than on cross-border VCs when terminating investments abroad. Their examination reveals that cross-border VCs terminate their investments efficiently and they are less likely to escalate from investments, compared to domestic VCs. Moreover, previous studies have defined the duration of cross-border VCs engagement with investee companies as indicative of their tolerance for failure. These studies argue that a higher tolerance for failure is essential for firms to foster innovation, as increased tolerance can incentivize more innovative endeavours (Holmstrom, 1989; Manso, 2011). Tian and Wang (2014) provide evidence that a VC investor’s tolerance for failure can have a positive relationship with a start-up firm's innovation-related productivity. Furthermore, Luong et al. (2017) illustrate that when foreign institutional investors protect managers from the aftermath of failed innovations, it encourages a framework for failure tolerance. As a result, managers are less concerned about their career and reputation, allowing them to focus more on pursuing long-term, risky investments in innovative projects and thus facilitating innovation within investee firms. Therefore, I argue that cross-border VCs experience less emotional attachment and less social pressure from the local community during the decision-making process. Thus, cross-border VCs are more likely to give more time to investee companies growing and achieve innovation.

Moreover, I speculate that with less emotional attachments to investee firms, cross-border VCs monitor investee companies externally, reducing agency problems, mitigating individual decision bias, and spurring innovation as a result. The agency problem is common in growing firms when ownership and management are separated. The theory of Stein (1989) indicates that managers could underinvest in innovative projects considering the high risks and the inability to generate predictable returns in the short run from innovative projects. The agency problem in VC investments is shown from four perspectives. Initially, entrepreneurs may not consistently employ maximal effort to optimize profits. Additionally, entrepreneurs possess a superior understanding of their products, giving rise to the information asymmetry problem. Furthermore, VCs prefer to assume decision-making authority in instances of disagreement. Moreover, entrepreneurs retain the capacity to exert influence over VCs by leveraging the potential departure as a crucial reservoir of valuable human capital for the company (Kaplan and Stromberg, 2004). Specifically, the interest conflicts between maintaining firm short-term profitability or pursuing their private benefits, managers may underinvest in innovation projects and use the budget for other projects, which earn more profits for their benefits (Luong et al., 2017). This is harmful to firms' innovation development and long-run performance. In addition, Bena et al., (2017) claim that because of less contact with corporate insiders than domestic institutions, foreign investors, as external monitors, can reduce managerial entrenchment and promote investment in riskier opportunities for growth and Gillan and Starks (2003) indicate that foreign institutional investors play a more important role in corporate governance than domestic peers because of their independent position and a lack of conflicts of interest. Comparable to foreign institutional investors, cross-border VCs invest outside of their home countries and have less contact with investee firms' local economics, so I expect that cross-border VCs can monitor portfolio firms as effective external monitors and reduce agency problems and then increase innovation. Furthermore, based on the data and available information, with the supervision of the investment committee, cross-border VCs make rational decisions, regardless of emotional attachments and concerns (Benson and Ziedonis, 2010; Devigne et al., 2016), leading to more rational and objective decision-making from cross-border VCs than from domestic VCs, less individual decision bias, and resulting in innovation increase.

ii. Distinct Risk Management Mechanism

Secondly, besides less emotional attachments to investees, I argue that cross-border VC investments are made for a different purpose compared to domestic investments. Cross-border investors implement a distinct risk management mechanism, in consequence, more tolerance for investments and boosting investee company innovation. Previous studies demonstrate that entering a foreign market, cross-border VCs are motivated by the higher growth potential of investee companies and a new international market (Baygan and Freudenberg, 2000; Guler and Guillen, 2010), especially the high innovative and substantial growth opportunities of the portfolio companies in the foreign market (Dai et al., 2012). Moreover, some cross-border VC investments are for global portfolio diversification purposes (Bena et al., 2017; Buchner et al., 2018), particularly for investors with predominant allocations in domestic ventures (Poterba and French, 1991). Therefore, managing risks involved due to the geographic distance, cross-border VCs utilize their own distinct risk management mechanism in investments. For instance, Wright et al. (2005) examine that cross-border VCs make significant different risk assessments and information sources used in targeted selection from domestic investors. In addition, cross-border VC investors diversify some risks away within the international portfolio (Bena et al., 2017). Cross-border VCs' effective implementation of a specialized risk management mechanism enhances their capacity to proficiently manage risks and costs arising from geographic distance, and less concerned about returns and performance of global investments (Buchner et al., 2018). I expect more tolerance and greater risk appetite from cross-border VCs to investee companies, in terms of more time and more money for innovation projects which motivates innovation ultimately. According to previous literature, people with a great risk appetite are willing to take more risks and are more likely to inspire innovations; Hirshleifer et al. (2012) show that overconfident CEO make riskier options and increase innovation; Sunder et al. (2017) argue that CEOs with pilot credential are willing to take more risks and open to new ideas, as a result, generating more innovation and patents. Hence, I expect cross-border VCs to manage risks better and then simulate innovations.

iii. Enhanced Knowledge Diffusion

Thirdly, I argue that cross-border VCs increase innovation through knowledge diffusion in both firm level and country level.

On the firm level, I presume cross-border VCs, equipped with industry and professional insights, can consult investee firms to identify core strengths, and develop innovation efficiently. Previous studies find evidence that patents become more focused in the years after private equity investment (Lerner et al., 2011). Private equity investors identify portfolio firms' business strengths and develop them into business core comparative advantages. Instead of keep investing in developing completely innovation projects, Lerner et al. (2011) argue that private equity investors use available resources to adjust strategies and then increase innovations efficiently, shown as increasing the number of patents and citations. Compared to private equity, VCs make investments efficiently in firms with high growth and innovation potentials (Guler and Guillen, 2011; Chemmanur et al, 2011; Tian, 2012; Dai et al., 2012). Furthermore, VCs help investee firms distinguish their business opportunities. In fact, as shown by Kaplan and Stromberg (2004) VCs help shapes the strategy and business model before investing and expect to be active in these areas afterward. In the aspect of cross-border VC, Wright et al. (1992) and Murray (1995) explore the UK VC investors' cross-border investments, they find that UK venture capitalists enter the new market abroad with their comparative advantage of accumulated experience and expertise over local competitors. Besides, cross-border VCs integrate multi-cultural perspective to investee firms' strategic development, and eventually impact company innovation. Devigne et al. (2013) suggest that cross-border VCs support portfolio companies to enter international markets by leveraging their knowledge and legitimacy. Therefore, I speculate that cross-border VCs convey worldwide insights and multi-cultural perspective to investee companies, and then facilitate companies to identify their core business advantages and develop international strategies and business model. As a result, cross-border VCs guide investee companies to realize its high innovation and growth potentials.

In addition, based on resource based theory, a company is a collection of resources and how valuable these resources are, determine the competitive advantage of the company (Barney, 1986, 1991). In particular, companies endowed with more valuable, scarce, and unique resources are anticipated to establish a robust competitive advantage, outperform their resource-constrained peers and demonstrate superior growth over time (Barney 1991; Chandler and Hanks 1994; Cooper et al. 1994, Devigne et al., 2013). Makela and Maula (2005, 2006) and Devigne et al. (2013) indicate that in contrast to domestic VC investors, cross-border VC investors support the portfolio companies with more diversified resources, beyond local community, for company growth and development. Furthermore, González-Uribe (2020) and Bubna et al. (2020) specify the transferable knowledge resources are vital for innovation. They suggest that knowledge and innovation are transferable and exchangeable between entities, for instance, within the VC community, and knowledge transferring is associated with innovation increase. Therefore, I conjecture that cross-border investments facilitate connections between cross-border VCs and investee companies that extend beyond financial transactions. Cross-border VCs transfer knowledge and share resources with investee companies, thereby eventually spurring innovation.

Besides firm-level resources, cross-border investments also communicate innovation resources and technologies at the country level. Cross-border VCs build a connection for firm-level resources as well as country-level resources for knowledge sharing and diffusion. To be more specific, countries with high innovation records are considered to have better infrastructures, institutional designs, and human capital pools, while investees from low-innovation countries benefit from accessing these innovation supportive resources to increase their innovation (Luong et al., 2017). Therefore, cross-border VCs from high innovative to low innovative countries make the resources abroad available for portfolio firms through their investments, such as invention teams, research outputs, and advanced technologies in parent firms. For example, Chahine et al. (2022) indicate that U.S. VCs have access to research generated in their home country, and then convey the research, benefiting the innovation levels of their investee firms who are from OECD countries. In addition, Hsu et al. (2021) indicate that in cross-border M&As, acquirers in low-innovation countries are more likely to engage in cross-border M&A, and firms from low-innovation countries produce more patents and invest more in R&D after they acquire targets in high-innovation countries. Through cross-border investments, investee firms in low-innovation countries can learn from the advanced technologies and build more innovations based on the innovation-supportive environment. Therefore, I expect that the cross-border VC investments from high innovation country carry the knowledge and diffuse to investee companies and increase investee company innovation

In summary, as cross-border VCs exhibit less emotional attachments with local environment, at the same time, more engagement and commitment to investee companies, and externally monitoring investee company; cross-border VCs implement distinct risk management mechanism, due to the purpose of portfolio diversification, with less concern and more tolerate; in addition, cross-border VCs connect and diffuse knowledge from firm level and country level, I make the hypothesis that

Hypothesis 1: Cross-border VCs have a greater impact on investee company innovation than domestic VCs.

3.3. Data

In this part, I illustrate the databases used in this work, sample selection process and variable constructions.

3.3.1 Database

Refinitiv Eikon, provided by Thomson Financial, is the primary data source for VC information, and it has been used extensively in VC research (Hochberg et al., 2007; Dai et al., 2012; Bernstein et al., 2016; González-Uribe, 2020; Ma, 2020). I download VC data from the Private Equity Module of Refinitiv Eikon (formerly VentureXpert). This database includes information on worldwide venture capital investments since 1980. It shows detailed information on the company level and deal level, such as the information on investor companies, investment date, investor and investee firm nations, investment stage, investor types, and so on.

I collect innovation data from Bureau van Dijk's Orbis database, specifically, the Intellectual Property database (Orbis-IP), which contains all patent applications since 1900. Orbis-IP has been used in many research for innovation studies recently (Konara et al, 2022; Deng et al, 2022; Nathan and Rosso, 2022). In the company-level data, Orbis provides company information including geographic information, financial statements, ownership information, and patent portfolio, which includes the number of patents, value, and indicators for patents. The patent level data, contains the patent owner, citations, and transaction information. The patent data is taken from Orbis and gathered from the world's major patent offices, including the UK, European (EPO), US, Patent Corporation Treaty (PCT), and other offices.

Following Luong et al. (2017) and Hsu et al. (2021), I obtain country data from World Development Indicators (WDI) and Word Bank database. I collect GDP, population, market capitalization, the number of listed domestic companies, patents applications by residents, and imports, exports data for each country in each year in the sample period.

3.3.2 Sample Selection

The sample selection process is as follows. First, I collect the universe VC investment data from Eikon. Iriyama et al. (2010) and Khurshed et al. (2020) suggest that the globalization of VC only began to gather pace in the mid-1990s. Following their studies, I download the deal level VC investments data from Eikon since 1996. Then I filter the data to include only VC investments that begin with the initial funding round and are completed within one year, as this stage plays a crucial role in VCs' selection, evaluation, and other key strategic decisions (Li et al., 2014). Furthermore, tracking the outcomes of the first-round investment, can alleviate other causes for the innovation performance changes and reverse causality. Therefore, following their studies, I filter the sample by setting the start round equal to 1 and then track the corresponding innovation outcomes through the end of 2020.

I first identify 29,610 VC investments from Refinitiv Eikon and successfully match 20,025 of them in the Orbis database, achieving a match rate of approximately 70%. After excluding companies not listed in the Orbis-IP patent database, the final sample consists of 10,844 investment cases across 69 investor nations and 72 investee nations. Of these, 8,965 are domestic VC investments and 1,879 are cross-border VC investments.

i. Subsample

In addition, Chemmanur et al. (2014) examine a subsample of firms that generate at least one patent prior to or after investment, given the concern that a large number of firms never file a patent in their sample. Tian and Wang (2014) also use firm-year observations with positive patent counts as the subsample. Similar to these studies, considering the time required for the first patent grant is crucial, I select observations with at least one patent in the sample period as the subsample, to better see the effect of the VCs on innovation by number of patents. The subsample of observations with positive patent counts, reduces the sample size to 1,562 observations. The median patent count per year is 2 and the mean is 6. On average each patent receives 6 citations.

ii. Merge and Matching

I use investee company name as the common identifier to merge investee companies' investment data from Eikon with their patent data from Orbis. I conduct four steps in merge and matching. First, I standardize company names for both Eikon and Orbis, by converting all letters to lowercases, and dropping the special symbols in the names and the suffixes and prefixes. Second, I use "matchit" in Stata to fuzzy match the investee company names from Eikon and patent company names from Orbis. Based on the company names, "matchit" will generate all the possible fuzzy matching results for each entry, and there will be a matching similarity score for each match, from 1 to 0. A higher similarity score indicates a higher similarity of the matching, and 1 indicates exact match. I use 0.7 as the benchmark of the matching results similarity score. I drop the matching results where similarity scores are lower than 0.7, and then I check the results left. If there is only one matching results, I keep it as the "successful match". Otherwise, I keep the highest score or the same city of the matching results. And then I leave the rest for the further matching using algorithm in Orbis. Third, I use algorithm in Orbis to further match. Following the matching process by Yan et al., (2021), I use the build in matching function in Orbis to process fuzzy match and find the BVD identifier (BvDID) in Orbis by the matching firms names and addresses. Specifically, I use the search function of the BVD Orbis database, which is submitting a list of firms to BVD system with the city and nation information, and then a matching process produced a set of firms that best matched the specified search criteria. Then I obtain the BvDID, the identifier used in Orbis and Orbis-IP. Furthermore, based on BvDID, I will be able to track patent information in Orbis-IP.

Next, I check all the matching results. The matching and checking process is inspired by the matching process by Ma (2020), which is that if an exact match is identified, it will be considered as a “successful match”. To be more specific, if an exact match of stem names is identified, and the two companies are located in the same city and state, this will be regarded as a “successful match”. Otherwise, I consider this as a “potential match”, and then manually check the matching results by screening the available public information.

In this research, I use the Batch search in BvD, and it can look up for up to 1000 companies each time. There are about 100 companies exact match identified by the system, which is seen as the “successful match”, as mentioned above, and the rest matches are seen as the “potential match” left for checking. There are three scenarios about the “potential match” waiting for further check. Firstly, if there are more than one matching result shown, I choose the matching company with the exact headquarter address, and then move it to the “successful match”.

Secondly, if the matching pair has similar name but not exact matching names, and the cities and state is the same, or if the company name provided by Eikon is as same as the previous company name saved in Orbis, and they are located in the same city and state, it is considered as a “successful match”.

Lastly, for the matched pair with same or similar names, but located in the different cities, following Block et al. (2014), I make judgement by the address zip code, the cities in Google map, and the company business industry. The city information is shown at a different level in Eikon and Orbis according to different countries. Therefore, I use headquarter address, zip code, and google map to check if the company headquarter matches. Furthermore, I incorporate the business industry information as a reference for further check. Pairs confirmed as successful matches through the manual check are moved to the “successful match” set. Otherwise, it will be seen as “failed to match”, such as missing city or nation information in either side, or no matches found.

As a result, I have checked 29,610 investee companies from Eikon, and there are 20,025 companies matched with their BvDIDs, which is about 70% of the firms matched successfully. And then using the matching bridge file, I merge patent data with the VC data, and removed companies not included in the patent database. Although around 30% of firms could not be matched, these unmatched observations are likely to be concentrated among smaller firms and start-ups with limited disclosure and incomplete database coverage. Since these firms are primarily missing because of data availability rather than because of characteristics directly related to the analysis, the unmatched portion is unlikely to generate substantial selection bias. Accordingly, while unmatched observations cannot be entirely ignored, they are unlikely to materially affect the representativeness of the final sample. After main sample selection, the final main sample consists of 10,844 investments.

3.4. Variable Definition and Construction

3.4.1 Dependent Variable: Innovation

In this study, I utilize three dependent variables in the analysis: the number of patents, the number of citations these patents received following a VC investment, and the number of citations per patent measured over the observing windows (Tian, 2012; Luong et al., 2017; Ma, 2020).

Some studies use R&D expenses measuring innovation (e.g. Chahine et al., 2022), since R&D expenditures indicate innovation input. However, R&D expenditures only measure innovation input rather than output. Some R&D investments do not lead to patent granting eventually (Luong et al, 2017). In the "Fields of Intellectual Property Protection", the World Intellectual Property Organization (WIPO) indicates that only useful, novel, and nonobvious inventions are patentable subjects (2004). This suggests that not all R&D investments eventually generate meaningful and successful patents output. Thus, R&D expenditure is not a measurement for innovation in this study. In addition, different firms may share the various standards for information and financial statement disclosure globally. Many firms do not disclose R&D expenses in their accounting and financial statements according to their accounting standards. However, missing R&D expense record does not indicate that the firm did not involve in any innovation activity (Koh and Reeb, 2015; Luong et al, 2017). Therefore, considering innovation output and various information disclosure standards across world, I use patents quantity and quality to measure innovation instead of R&D expenses.

a. Innovation quantity

Researchers have claimed that the most important measure of firms' innovation output are patent counts (Griliches, 1990; Bena et al., 2017). Therefore, the first measure is the number of application patents to measure the innovation quantity, which is defined as the number of patents applications that are eventually granted for a firm in each year. For the date for the patents, there are several dates for choosing, filling date, publication date, grant date, expiration date, and priority date. The earlies date is the priority date, which indicates that the first year an application enters any patent offices in the world. According to previous studies, instead of grant years, I use application year as the date for innovation, which is the closest date to record the invention, and better captures the actual time of innovation compared to grant year (Griliches, 1990; Bernstein et al., 2016; Luong et al., 2017; Ma, 2020; Nathan and Rosso, 2022).

Furthermore, Lerner et al. (2011) and Tian (2012) point a problem with the patent counting is the truncation problem, which is that some patents applied around the sample cut-off time are still under view or not granted yet are missing in the patent database. The truncation bias is shown as the number of patents becomes is lower towards the end of the sample period. Luong et al. (2017) address the truncation bias by adjusting the study period ending year. Specifically, they end study period for investments in 5 years advance to the patent study time, so that there is a 5-year time to observe the impact of the last investments. I followed them to adjust the study period for VC investments so that I leave enough years and window time for the last VC investments. In this study, if investments made in 2015, it would have 6 years to wait for applications be granted and receive citations, so that the 3-year and 5-year windows are applicable for these investments. The number of patents is denoted as Patents in tables. An issue with the number of patents is the right skewness of the distribution of patents grants in the sample, with the median at 0. The similar observation and issue is also shown in the previous innovation literature (Seru, 2014; Tian and Wang 2014; Luong et al., 2017). To fix the skewness problem mentioned by Griliches (1990), I follow Ma (2020) and use the natural logarithm of one plus this value, which is noted as LnPATENT.

b. Innovation quality

The second measure is the number of citations the patents received in the following years after application, measuring the innovation quality. I track the citations count in the calendar year of the patent grant and the 3 subsequent years, which is referred to as “3-year window” by Lerner et al. (2011). This variable is constructed to assess the importance of the innovation and patents, and the more citation received by the patents, the more impact and influence made by the innovation, indicating a high innovation quality. The number of citations is the number of forward citations, which are cited by other patents which are granted later, denoted as CITATION in tables. Following the methods in previous studies (Ma, 2020; Lerner and Seru, 2022) and similar to the natural logarithm of one plus the number of patents, to fix the right-skewness of the data, I use the logarithm of one plus this citation count, denoted as LnCITATION. In addition, following Tian (2012), I use citation per patent to capture the patent impact, noted as Citation/Patent and logarithm of one plus Citation/Patent, as LnCIT/PATENT.

3.4.2 Main Independent Variables: Cross-Border VC and Domestic VC

Consistent with Devigne et al. (2013), Li et al. (2014), and Chemmanur et al. (2016), I define cross-border VC investments (CBVC) using a binary independent variable. Specifically, the variable takes the value of 1 if at least one VC in the investment syndicate is headquartered in a different country from the investee firm, and 0 otherwise. Additionally, for robustness checks, we calculate the percentage of cross-border VCs in the investment syndicate (Perc_CBVC) as an alternative measure, following the approach used by Chemmanur et al. (2019).

3.4.3 Control Variables

Following the research about innovation, I control for VC characteristics, deal characteristics, and investee country macroeconomics conditions which eventually influence investee company’s innovation productivity.

For VC and deal characteristics, I control for the number of VCs investing in that year, VC age, fund age, investment size, and investment stage. Tian (2012) finds that VC syndication is related to firm innovation, concluding that by utilizing multiple resources, skills, and information, syndicated VCs invest more in R&D intensive and riskier firms than standalone, which leads to investee firms end up with higher innovation productivity and higher growth. Based on this research, I include the effect of syndication in the analysis, using the number of VCs (NumVCs) investing in that year in the control variables. In addition, VC age and fund age will influence innovation. Tian and Wang (2014) argue that young and less experienced VCs are eager to establish a track of success, and then they are less tolerant of failure than old and experienced VCs, which lead to less innovation. They provide evidence that young VCs are concerned about careers and capital constraints, which leads them to make conservative decisions and less innovation for investee companies as shown in the results. In addition, Cong and Xiao (2022) build a model and suggest that funds with recent success have more failure tolerance and motivate innovation. Therefore, VC age and fund age are related to the likelihood of developing innovation, and I use the natural logarithm of VC age (LnVCAge) and fund age (LnFUNDAge) as control variables in the analysis. Following Tian (2012), I also include natural logarithm of the VC investment size (LnINVSize), and the development stage of the investee firm at the investment date, captured by a categorical variable with the startup/seed stage as the reference category (DevSTAGE), including Startup/Seed, Early Stage, Expansion, Later Stage, and Buyout/Acquisition.

At the country characteristics, I incorporate various controls derived from existing literature that could potentially influence firm innovation. Hsu et al. (2014) establish a relation between financial development and innovation. Therefore, I include a control for equity market development, measured by the ratio of a country's stock market capitalization to its gross domestic product (MARKETDev). Additionally, I incorporate the investee company country's GDP per capita (LnGDP), following the control variables used in the research by Loung et al. (2017).

3.5. Summary Statistics

Table 1.1 Panel A presents the distribution of VC ownership, showing 17.33% of the sample deals are involved with cross-border VC investors. Panel B summarizes innovation output of investee companies within 3- and 5-year windows. On average, companies generate 2.7 patents with 1.4 citations per patent within 3 years of VC investment and 4.7 patents with 1.6 citations per patent within 5 years. When comparing domestic and cross-border VC-backed companies, cross-border VC-backed companies produce more patents, averaging 4.8 compared to 2.3 patents for domestic VC-backed companies. Patent impact, measured by citations and citations per patent, shows a similar pattern: cross-border VC-backed firms receive 1.6 citations per patent on average, while domestic VC-backed firms receive 1.4, within a 3-year window. These trends persist in the 5-year window and align with findings from Chemmanur et al. (2014). Panel C presents the patent variables means by groups, showing that cross-border VC investments generates significant more patents and citations counts than domestic VC investments in 3-year and 5-year window.

[Table 1.1: Descriptive statistics]

Furthermore, Panel D summarizes the control variables, including VC investors, investments, and investee country characteristics. The average age of VC investors is 14 years, and the mean fund age is 9.6 years. On average, VC investments amount to 2.44 million dollars, consistent with the findings of Devigne et al. (2016). Regarding investee country characteristics, the mean GDP is 5,320 billion dollars, with the natural logarithmic transformations of GDP per capita of 9.98, and the average stock market capitalization as a proportion of GDP is 0.949, similar to the values reported in Buchner et al. (2018).

Panel E outlines the development stage of the investee companies at the time of VC investment. About 47.57% are in their seed and early stage, while 44.15% of the companies are in their expansion or later stage, reflecting a similar distribution to Devigne et al. (2016). Furthermore, Table 1.2 shows the correlation matrix. The correlation between innovation variables and cross-border VCs dummy variables are negative, suggesting that cross-border VCs are more likely to invest in low innovation investee companies, seeking growth opportunities. In addition, a positive correlation between cross-border VC investments and VC age indicates that older and more experienced VCs are more likely to make cross-border investments than young VCs, consistent with findings by Buchner et al. (2018). Cross-border VCs also invest in a significant larger size than domestic VCs, aligning with findings illustrated by Devigne et al. (2016).

[Table 1.2: Correlation Matrix]

Moreover, I run the summary statistics for the subsample. As shown in Table 1.3, in the subsample, which are the investee companies have at least one patent in 3 years after receiving VC investments, the summary statistics for all variables are consistent with the main sample.

[Table 1.3: Summary statistics_subsample]

In addition, the t-test of variables indicates differences between domestic VCs and cross-border VCs, as results shown in Panel C. Panel C indicates the same finding with the main sample, which is that aged VCs are likely to make cross-border investments, and cross-border VCs are more likely to invest in a larger size than domestic VCs. In addition, companies backed by cross-border VCs demonstrate significantly higher innovation abilities, reflected in increased the natural logarithm of one plus the innovation variables. Companies that have received investments from cross-border venture capitalists demonstrate both a higher quantity and quality of innovation. Furthermore, the correlation matrix in Panel D indicates the negative relation between cross-border VCs and investee company innovation outcomes, in align with the main sample.

3.6. Empirical Tests and Methodology

I use OLS model as the baseline model to test the relationship between cross-border VCs and innovation.

3.6.1 Baseline Model

This study aims to investigate the relationship between cross-border venture capital and the innovation output of investee companies, and I use pooled ordinary least squares (OLS) regressions in the baseline test. However, there exists a plausible concern regarding potential selection bias inherent in OLS regressions. Cross-border venture capitalists might strategically invest in ventures with superior growth potential or foresee heightened innovation prospects, potentially influencing the observed positive correlation between cross-border venture capital and innovation output. To mitigate this concern, following Hsu et al. (2014), Bena et al. (2017), and Loung et al. (2017), I employ regressions incorporating portfolio company industry, investment year, and investment stage fixed effects, effectively adjusting for unobservable, time-invariant firm disparities. Furthermore, I conduct Heckman two-stage analysis to mitigate bias from selections.

Equation 1: Baseline model for innovation quantity

$$\mathbf{Ln(PATENT)}_{j,t+3} = \boldsymbol{\alpha} + \boldsymbol{\beta}_1\mathbf{CBVC}_{i,t} + \boldsymbol{\gamma}\,\mathbf{Z}_{j,t} + \mathbf{Industry}_{j,t} + \mathbf{Year}_{t} + \mathbf{Stage}_{j,t} + \mathbf{v}_{j}$$

Equation 2: Baseline model for innovation quality

$$\mathbf{Ln(CITATION)}_{j,t+3} = \boldsymbol{\alpha} + \boldsymbol{\beta}_1\mathbf{CBVC}_{i,t} + \boldsymbol{\gamma}\,\mathbf{Z}_{j,t} + \mathbf{Industry}_{j,t} + \mathbf{Year}_{t} + \mathbf{Stage}_{j,t} + \mathbf{v}_{j}$$

In the equation 1 and 2, "i" denotes the VC firm and "j" is an investee firm that is financed by VC-i. Z represents the control variables capturing VC, deal, and country characteristics that may influence innovation. Industry, Year, and Stage are variables for industry fixed effects, fiscal year fixed effects, and stage fixed effect. In all regressions, I report in parentheses robust standard errors clustered at the investee company level and the results are displayed in Table 1.4.

[Table 1.4: OLS regression]

Table 1.4 illustrates the OLS regression results of the effect of cross-border VCs influence innovation. The main outcome variable is investee company innovation, specifically, innovation quantity and innovation quality, measured by natural logarithm of the number of patents, as shown in Column (1) and Column (2), natural logarithm of number of citations in Column (3) and Column (4), and natural logarithm of number of citations per patent in Column (5) and Column (6) in Panel A and B.

The main variable of interest is the ownership of cross-border VCs, using cross-border VC dummy variable as the proxy in Panel A and the percentage of cross-border VC in Panel B, respectively. In Column (1), I report the results of the positive relation between cross-border VC dummy and the number of patents, with the year, industry, and stage fixed effect. Furthermore, I add the control variables for deals, investors, and country characteristics, I observe that the positive insignificant coefficient for dummy variable of cross-border VC in Column (2). In another word, the results suggest that cross-border VC's do not show a significant impact on innovation change in 3 years. Furthermore, I test innovation quality by the number of citations and number of citations per patent. As the results shown in Column (4) and Column (6), the estimated coefficient for cross-border VCs is positive insignificant. This suggests that cross-border VCs have no significant different influence as domestic VCs on the company patents and citations.

For the investor characteristics, the number of VCs, and investment size show a positive and significant coefficient in the regression, which is consistent with the finding by Tian (2012), indicating that number of investing VCs has positive relation with innovation and more investments encourage more innovation. For the country characteristics, the country GDP per capita and country Equity, which is measured by stock market capitalization divided by GDP, have positive relations with ventures innovation. This finding consists of the study of Hsu et al. (2014).

In addition, I use an alternative measure for the cross-border VC ownership, the percentage of cross-border VCs, calculated by the number of cross-border VCs divided by the total number of VCs. In Panel B, the estimated coefficients for cross-border VC dummy are positive but insignificant for the number of patents and citations. Therefore, I observe that a higher percentage of cross-border VCs does not significantly influence a greater number of patents and a higher innovation.

I also use different measuring window for patents and citations, as 5-year window. The results are presented in Table 1.5.

[Table 1.5: Different windows]

I observe consistent results when employing a 3-year window for analysis. Overall, the baseline results suggest that cross-border VCs do not significantly increase venture innovation more than domestic VCs, in terms of number of patents and citations. These results do not support for the hypothesis, indicating that the cross-border VCs are not significant different from domestic VCs on investee company innovation.

While in the subsample, in Table 1.6 Panel A, I observe that the positive and significant coefficient for dummy variable of cross-border VCs to the number of patents and citations.

[Table 1.6: Subsample baseline]

Specifically, the dependent variable in the first two columns is the number of patents. The estimated coefficient of cross-border VC dummy in Column (1) is positive and significant at 1% level, and after adding control variables, the coefficient estimate in Column (2) is positive and significant at 5% level, suggesting that investee company increases innovation after receiving cross-border VC investments. The dependent variable for Column (3) and (4) is number of citations. The coefficient estimate of cross-border VC dummy variable in Column (3) is positive and significant at 1% level, and the coefficient estimate is positive and significant at 5% level after controlling for deals, investors and country characteristics. Specifically, investee companies who receive investments from cross-border VCs will have about 25% increase in patent output comparing to the companies that receive investments only from domestic VCs. Furthermore, the investee companies will increase 36% more citations after receiving investments from cross-border VCs than from domestic VCs. Furthermore, in Column (5) and (6), I use the citation per patent to measure innovation, and the coefficient estimate is positive and significant at 10% level for cross-border VCs dummy before adding control variables. The results in Table 2.3 indicate that for the investee company with patents, cross-border VCs has a greater impact to increase the investee company innovation in both number of patents and citations and the results significantly support the hypothesis.

The main variable of interest in Panel B is the percentage of cross-border VCs. I report the results in Panel B, similar to the results in Panel A, the coefficient estimates of percentage of cross-border VC for all innovation measurements, the number of patents, number of citations, and citations per patents, are positive and significant. Specifically, the estimated coefficient in Column (1) is positive and significant at 1% level, and positive and significant at 5% level after adding control variables, shown in Column (2). It suggests that more cross-border VCs investing, investee company generates more patents. One percentage of cross-border VC increases, lead to increase natural logarithm of the number of patents by 0.258. Moreover, I observe that the percentage of cross-border VCs are significantly positive related to company citations. The results from Column (4) and Column (6) suggest that coefficient estimates of percentage of cross-border VC for number of citations, and number of citations per patent are positive and significant at 1% level and 5% level respectively, after adding control variables. Therefore, I conclude that within investee companies with patents, cross-border VCs significantly increase their patents and citations more than domestic VCs.

The results are consistent using 5-year with the results using 3-year window, shown in Table 1.7.

[Table 1.7: Different windows]

Panel A presents the results of using 5-year windows. After adding control variables, and industry, year, and stage fixed effects, I observe the positive and significant estimated coefficients for cross-border VCs dummy for both number of patents and citations, in Column (2) and Column (4). Furthermore, through Columns (7)-(12), the main explanation variable is percentage of cross-border VCs. The estimated coefficients for the percentage of cross-border VCs are positive and significant at 1% level for number of patents and positive and significant at 10% level for the number of citations, suggesting a higher rate of cross-border VCs ownership leads to a higher number of patents and citations. In addition, I find that the estimated coefficient for citations is higher than that for patents. Cross-border VCs increase citations in a higher magnitude than patents. The results suggest that coefficients for cross-border VC dummy variables, and percentage of cross-border VCs variables are positive and significant, consistent with other windows.

Therefore, I conclude that in the subsample, companies with positive patent counts, the percentage of cross-border VCs are positive and significant relation with number of patents as well as citations, and cross-border VCs, and cross-border VCs have a greater impact on company innovation than domestic VCs.

3.6.2 IV & Heckman Two-Stage

The coefficient estimate of the cross-border VCs dummy variable is insignificant positive for the number of patents in the OLS regression. However, there is a valid concern regarding the potential presence of selection bias inherent in OLS regressions. VCs invest abroad for high innovative potentials of the investee companies to grow in future (Guler and Guillen, 2010; Dai et al., 2012). In addition, due to the saturated domestic market, VCs are seeking new opportunities in other countries (Buchner et al., 2018). As shown in Table 1.10, most cross-border investments are made from high innovation country to low innovation countries. Therefore, the investee companies, receiving cross-border investment, are likely to be a growing and low innovation companies, which don't have a patent when cross-border VCs invest and are far from achieving any innovation output such as patents and citations. Therefore, the selection of investee companies with high innovation potential, induces the downward bias in OLS estimates. Similar downward bias is also shown in the study by Tian (2012). The distribution of cross-border VCs confirms the selection bias process and is the main driving force that biases the coefficient estimate downward. Following Tian (2012) and Chemmanur et al. (2011), I adopt the Instrument Variable and Heckman two-step estimation method in this section to address the biases in the analysis.

I implement a generalized version of the traditional Heckman model, and the detailed version is in Heckman (1979) and Maddala (1983). In the model I use inverse Mills ratios to capture the effect of unobservable which may be used by VCs when making cross border investment decisions. To be more specific, I use the first stage probit regression to predict the probability of a given deal being a cross-border investment and the inverse Mills ratio for cross-border VCs and domestic VCs. Previous literatures use the inverse Mills ratio as a measure of unobserved factors that affect the selection of firms for treatment (Tian, 2012; Buchner et al., 2018), which is cross-border VCs in the context, as well as outcome variable, which is post-VC investment innovation output in the context.

In practice, in the first stage, the dependent variable is the dummy variable of cross-border VCs, that equals one if there is a cross-border involved in the deal, and zero otherwise. Following the instrument suggestion of Wolfords and Siegel (2019) and building on Buchner et al. (2018), I use capital inflow into the VC domestic industry as the instrument in this initial estimation. The relevance of this instrument arises from the fact that higher capital inflows expand the supply of venture funding in the home market, intensify competition for domestic investments, and reduce the relative marginal return to additional domestic investments. As a result, VCs facing more abundant capital in their home market have a stronger incentive to seek investment opportunities outside national borders. Furthermore, the exclusion restriction is plausible because domestic VC inflow is determined by aggregate financing conditions in the investor's home-country VC market rather than by unobserved characteristics of the foreign portfolio firm. After controlling for observable firm characteristics, deal attributes, and country-level factors, there is no strong reason to expect domestic VC inflow to directly influence the patenting outcomes or innovation performance of the investee company abroad. Its effect should operate through the selection of VCs into cross-border investments rather than through a direct innovation channel. Therefore, the VC domestic industry inflow is a validate instrument variable to examine the role of cross-border VCs on innovation outcomes.

Moreover, the explanation variables are the controls variables of deal, VC, and investee company country characteristics. In addition, I will have the inverse Mills ratio, which is the probability of the cross-border VC investment. Furthermore, in the second stage, I estimate investee company innovation outputs by including control variables and the inverse Mills ratio based on the estimates of the first stage among a range of control variables. To be more specific, the dependent variable is innovation output, which is measured by the number of patents and citations received within 3-years after investments in Column (1) and (2), respectively, and the main variable of interest is predicted dummy variable of cross-border VCs obtained from the first-stage regression. Heckman two-stage facilitates us to significantly minimize the VC firm's endogenous cross-border decision, resulting in an increase in the magnitude of the coefficient estimates. Moreover, the application of the Heckman (1979) Two-stage method enables us to address identification concerns and disentangle the impacts of selection and value-adding activities on the innovation output of investee companies.

[Table 1.8: Heckman Two Stage]

Table 1.8 presents estimations of Heckman two stage regressions, analysing the impact of cross-border VC investment on innovation outcomes. The first-stage probit regression in Column (1) estimates the probability of receiving cross-border or domestic VC investment. The results show a positive and significant coefficient for the number of VCs in the deal (NumVCs) suggesting a higher likelihood of cross-border VC investment in deals involving a larger syndication of VCs. In addition, the positive and significant coefficient of VC investment size (LnINVSize) indicates that the likelihood of cross-border VC investment increases with larger investment size. Furthermore, the positive and significant coefficient of VC industry inflow (Ln_inflow) suggests **that VCs are more inclined to invest cross-border when the domestic VC industry is expanding and reaching saturation.** Also, the negative and significant coefficient for stock market development of the investee company (MARKETDev), which is aligned with the expectation and Buchner et al. (2018) suggests that investees from less developed markets have a lower probability of attracting cross-border VC investment. Finally, the coefficient for the fund age (LnFUNDAge) is negative and significant at 10% indicating that older funds are less likely to engage in cross-border VC investments.

In the second stage of the Heckman regression analysis, I examine the effect of cross-border VC investment on innovation outcomes, while accounting for selection bias identified in the first stage. To this end, I incorporate the inverse Mills ratio as an additional control variable in the second stage. Columns (2)– (4) display the results with different innovation measures: the number of patents, number of citations, and citations per patent. The estimated coefficients for the predicted cross-border VC dummy variable (CBVC) are positive and significant at the 1% level for both patents and citation counts, supporting the main prediction that cross-border VCs have a greater impact on innovation outcomes. The coefficient of cross-border VC dummy variable (CBVC) for patent counts is 0.269, suggesting that cross-border VC investments are associated with a significant 30.7% increase in the number of patents compared to domestic VC investments. In addition, the estimated coefficient for investment size is positive and significant, suggesting that more investees receive generate more patents. Furthermore, the coefficients for log of country GDP per capita (LnGDP) is negative and significant.

The coefficient of CBVC for citation counts is 0.427 and positive and significant at the 1% level, suggesting that cross-border VC investments result in a notable 53.11% rise in citations, highlighting a strong positive relationship between cross-border VC investments and innovation. As in the control variables, I observe that a positive and significant coefficient for number of VCs (NumVCs). This suggests that having more VC investors involved significantly increases citations, consistent with the finding of Tian (2012) that VC syndication size is positively related with innovation outputs, for example, both patents and citations. In addition, consistent with patent counts, the estimated coefficient for investment size is positive and statistically significant, indicating that higher investment levels received by investee firms are associated with increased citations. However, the coefficient for citations per patent is not significant.

3.6.3 Supportive Tests

There are other tests for investigating how cross-border VCs increase innovation.

i. *Measuring failure tolerance: Investment duration of cross-border vs. domestic VCs*

I anticipate that cross-border VCs demonstrate a higher tolerance for failure, which in turn fosters greater innovation among their investee firms. To test this, I compare the failure tolerance of cross-border and domestic VCs by measuring investment duration. Specifically, I calculate VC's tolerance using their investment history, following the framework of Devigne et al. (2016). Investment failure is defined in three ways. First, a termination is assumed if a VC does not participate in subsequent rounds; Second, the focal round is considered the final round if no new financing or exit occurs within three years, the 75th percentile time to exit in the sample, as used by Devigne et al. (2016); and third, a failure is recorded if the investee company is classified as bankrupt or defunct (Tian and Wang, 2014). Based on these classifications, I compute the simple average investment period, weighted average investment period (adjusted according to the investment size), and the maximum investment period for each VC annually. This tolerance data is then merged into the main sample. The t-test results are presented in Table 1.9. Table 1.9 presents the t-test results, indicating that cross-border venture capitalists (VCs) have significantly longer investment durations than domestic VCs, aligning with the previous expectation. This suggests a greater willingness to remain committed to investee firms and a lower likelihood of premature withdrawal.

[Table 1.9: Test for tolerance for failure]

The simple average investment duration for cross-border VCs is 0.796 years, significantly exceeding that of domestic VCs at 0.721 years. This difference translates into roughly 27 extra days per investment. Although the average difference is modest, it is consistent with the greater complexity, monitoring costs, and coordination frictions associated with cross-border investing. The weighted average duration, adjusted for investment size, reveals a stronger difference between domestic and cross-border VC investments. Domestic VCs have a weighted average duration of 0.866 years, whereas cross-border VCs exceed one year, implying that larger cross-border investments remain active for around 2.6 months longer on average. This suggests that the longer duration of cross-border deals is not driven only by small or marginal investments; rather, it is more pronounced among economically more important deals. In turn, this pattern indicates greater dispersion in investment duration among cross-border VCs, with some investments being held substantially longer, particularly when more capital is committed. Moreover, the maximum duration is significantly greater for cross-border VCs (4.2 years) than for domestic VCs (3.3 years), a difference of more than one year, further suggesting that cross-border VCs are more likely to sustain a subset of investments for unusually long periods. Consistent with Devigne et al. (2016), I find that the presence of a cross-border VC significantly increases the maximum investment duration compared to domestic-only investments.

Therefore, the evidence suggests that cross-border VCs remain significantly longer with investee firms that ultimately fail compared to domestic VCs and cross-border VCs display greater failure tolerance and a lower tendency to withdraw capital prematurely, rather than a stronger propensity for commitment escalation. By allowing portfolio firms more time to develop despite early difficulties, cross-border VCs may create conditions more conducive to experimentation and innovation. Consistent with Tian and Wang (2014), such tolerance can support innovative activity by reducing pressure for immediate success and enabling firms to pursue riskier long-term projects.

ii. Cross-border VCs and knowledge diffusion

Furthermore, I posit that cross-border VCs from high-innovation countries foster innovation through knowledge diffusion. Using the Global Innovation Index (GII) by the World Intellectual Property Organization (WIPO) from the World Bank database, I categorize countries by innovation levels: high-innovation countries have an index above the 75th percentile, medium-innovation countries fall within the 25th to 75th percentile, and low-innovation countries are below the 25th percentile. Table 1.10 presents the country innovation level distribution with VC investments. Table 1.10 indicates that only 18.73% of cross-border VCs originate from lower-innovation countries targeting higher-innovation nations, such as low innovation country to medium and high innovation country, and medium innovation country to high innovation country. Consistent with González-Uribe (2020) and Matray (2021) on knowledge diffusion, the results support the argument that cross-border VCs enhance innovation through knowledge diffusion. Additionally, however, these investors target low-innovation but high-potential firms, introducing potential selection bias. To address this concern, I employ the Heckman two-stage approach in the estimations.

[Table 1.10: Knowledge diffusion]

3.7. Robustness tests

3.7.1 Different windows

Following Lerner et al. (2011), I extend the tracking period and track innovation output for up to five years after VC investments using Heckman two stage estimations. The results are presented in Table 1.11. In the first Column, I present first stage results, which is consistent with the results using the 3-year window. A positive and significant coefficient for the number of VC investors (NumVCs), indicates that cross-border VCs are more likely to invest in deals that involve a larger syndication of venture capital firms. In addition, a significantly positive coefficient for investment size (LnINVSize) shows that cross-border VC investment is more likely to occur in deals with larger investment amounts.

[Table 1.11: Heckman 5 year]

The coefficient for VC industry inflow is positive and statistically significant at the 1% level, aligning with expectations and prior findings based on a three-year window. As the domestic VC industry expands, investors increasingly seek opportunities abroad, reinforcing the positive relationship between industry growth and the likelihood of cross-border VC investments. Moreover, the coefficient for investee company country stock market development (MARKETDev) is negative and statistically significant, aligning with the expectations and supporting Buchner et al. (2018), indicating that firms in less developed markets are less likely to secure a cross-border VC investment. Furthermore, I present second stage estimations in Column (2)- (4). The results are similar to the 3-year window estimates, with positive and significant coefficients of cross-border VCs dummy variable for both patents and citations at the 1% level, demonstrating that cross-border VC investors significantly enhance company innovation outcomes.

The coefficient for patents (0.309) is higher than in the 3-year window, suggesting that a longer time horizon allows investee companies to generate more patents. The coefficient for citations remains comparable to the 3-year window results. Additionally, the number of VCs is positively and significantly associated with both patents and citations, consistent with Tian (2012). Similarly, larger investment sizes significantly boost innovation outputs, reinforcing prior findings. In addition, the positive and significant coefficient of the investee country's stock market development (MARKETDev) in citation counts suggests that a more developed stock market enhances citation counts. This finding aligns with Hsu et al. (2014), who report that a well-developed equity market fosters innovation. Furthermore, the coefficient for GDP (LnGDP) is negative and significant. The estimated coefficient of dummy variable of cross-border VCs (CBVC) is not significant.

3.7.2 Alternative independent variable

Rather than using a dummy variable, I quantify cross-border VC involvement as the percentage of cross-border VCs in each investment. This allows us to examine whether a higher proportion of cross-border participation leads to greater innovation. The Heckman two-stage estimation results using this alternative measure are reported in Table 1.12.

[Table 1.12: Alternative independent variable]

The results presented in the first-stage regression in Column (1) are consistent with those in Table 1.8, showing a positive and significant coefficient for VC industry inflow. This indicates that increased domestic VC activity makes VCs more likely to invest abroad. In the second stage (Columns 2–4), the percentage of cross-border VCs (Perc_CBVC) is positively and significantly associated with all innovation measures—patents, citations, and citations per patent. It is significant at the 1% level for patents and citations and at the 5% level for citations per patent. In addition, estimations for control variables are consistent with the results using dummy variables. These findings further confirm that cross-border VCs significantly enhance innovation outcomes compared to domestic VCs.

3.7.3 Poisson regression & Negative Binomial Regression

Recent studies by Chen and Roth (2024) and Cohn et al. (2022) suggest that using the log of one plus the outcome in linear regressions may lead to estimates with limited interpretability and incorrect signs for coefficients. They recommend using Poisson regression instead, as it provides consistent and efficient estimates under broader conditions, addressing the arbitrary unit-dependence effect. To account for this, I employ Poisson regression as a robustness test. I assume that the expected number of patents and citations follows exponential functions of the cross-border

VC effect (denoted as CBVC and Perc_CBVC in the table). The likelihood is estimated using the Pseudo-Maximum-Likelihood method. The results from the Poisson regression are presented in Table 1.13. The results indicate that cross-border VCs are significantly associated with higher innovation outputs, as evidenced by the positive and statistically significant (at the 1% level) coefficients for CBVC and Perc_CBVC. Specifically, the coefficient for the cross-border VC dummy variable (CBVC) is 0.721 for patent counts (PATENTS) and 0.588 for citation counts (CITATIONS), suggesting that the log of expected patent counts is 0.72 units higher, and the log of expected citations is 0.59 units higher for cross-border VCs compared to domestic VCs. In addition, consistent with the positive impact of cross-border VCs on patent and citation counts, the coefficient for citations per patent (CIT/PATENT) is positive, significant at the 1% level, and estimated at 0.268 in Column (3). This suggests that cross-border VCs are associated with a 0.27-unit higher log value of citations per patent relative to domestic VCs.

Additionally, the positive and significant coefficient for VC age in Column (1) and (2) suggests that older VCs have a greater impact on patent and citation counts. Regarding control variables, the results align with the main Heckman two-stage estimates in Table 1.8, confirming that larger syndication and investment sizes significantly enhance innovation outcomes. Moreover, the coefficients for GDP (LnGDP) and stock market development (MARKETDev) in Column 1 are negative and significant for patent count estimations, indicating an adverse impact on patent production. Similarly, Column (2) results show that fund age (LnFUNDAge) and stock market development (MARKETDev) exhibit negative and significant coefficients for citation estimates, suggesting a negative relationship between these factors and the number of citations. In Column (3), the positive and significant coefficients for GDP (LnGDP) and investee company stock market development (MARKETDev) indicate that higher per capita GDP and a more developed stock market in the investee firm's country enhance citations per patent, consistent with Hsu et al. (2014) and our Heckman two-stage estimation findings using a five-year window. In addition, the results suggest that younger VCs and funds increase citations per patent received.

Alternatively, I adopt the percentage of cross-border VCs (Perc_CBVC) as a measure of cross-border VCs involvement, with the results presented in Columns (4) - (6). The results are consistent with the estimates using dummy variable of cross-border VCs (CBVC). Specifically, the coefficients for Perc_CBVC are 0.749 for patents, 0.608 for citations, and 0.282 for citations per patent, indicating that a 10% increase in cross-border VC participation leads to respective increases of 7.78%, 6.27%, and 2.86%. These findings further confirm the significant contribution of cross-border VCs to investee firms' innovation outcomes compared to domestic VCs. In addition, the control variables' estimated coefficients are comparable to those obtained using dummy variables.

[Table 1.13 Poisson regression]

As also suggested by Cohn et al. (2022), the negative binomial model (similar to Poisson regression) maintains the same conditional expectations but relaxes the mean-variance equality restriction. This is achieved by explicitly modelling the variance as a separate gamma process, which allows for overdispersion. Therefore, negative binomial regression may be more efficient than Poisson regression in some cases, especially if the true variance is approximately gamma distributed. Accordingly, I also get estimates using negative binomial regressions in Table 1.14. The results indicate that all estimates for cross-border VCs are positive and statistically significant at the 1% level. For patent counts, the coefficient of CBVC is 1.094, implying that cross-border VCs are associated with a 1-unit higher log of expected patent counts compared to domestic VCs, controlling for other factors. Similarly, the log of expected citation counts is 0.8 units higher for cross-border VCs. Furthermore, the coefficient of Perc_CBVC for patent counts is 1.105, and that for the number of citations is 0.823, suggesting that a 10% increase in the share of cross-border VCs corresponds to an 11.68% rise in patent counts and an 8.58% increase in citation counts. These results slightly exceed those from the Poisson regression but remain consistent with prior findings, further supporting the positive impact of cross-border VCs on innovation outputs. Furthermore, I observe consistent results with previous findings, such as positive and significant coefficients for number of VCs (NumVCs), investment size (LnINVSize), GDP (LnGDP), and stock market development (MARKETDev). I do not find significant coefficients of cross-border VCs present for citations per patent in Column (3) and Column (6).

[Table 1.14 Negative Binomial]

3.7.4 Stacked Difference-in-Differences (DiD)

Furthermore, I employ stacked difference-in-differences (DiD) estimation methodology that exploits the average treatment effect on changes in innovation performance after cross-border VCs investments (treatment group), against similar innovation changes for investee companies without cross-border VCs investments (the control group). Instead of staggered difference-in-differences (DiD) regressions, I use stacked regressions to avoid potential bias from heterogeneous treatment effects or variation in treatment timing. For example, later-treated groups could act as controls before treatment occurs, while earlier-treated units can serve as controls after treatment.

Therefore, I follow the framework of Cengiz et al. (2019) and implement stacked DiD approach. Stacked DiD design restructures the data into a series of cohort-specific event windows to address the biases that arise in staggered treatment settings. For each treatment cohort, the method isolates an event-time dataset that includes the outcome variable, covariates, and all comparison observations that constitute "clean" controls within the relevant event window. These controls consist of units that remain untreated during the cohort's event window, not-yet-treated or never-treated units, as well as units treated in later periods, ensuring valid counterfactuals for each cohort.

Then these event-specific datasets are stacked together to form a single dataset. This structure ensures that identification for each cohort relies only on appropriate comparison groups, avoiding the problematic use of already-treated units as controls, which underlies bias in conventional two-way fixed effects estimators under heterogeneous treatment effects.

The final estimation proceeds by fitting a two-way fixed-effects difference-in-differences regression on the stacked sample, including dataset-specific unit and time fixed effects to absorb heterogeneity across cohorts and event windows. This procedure yields consistent estimates of dynamic treatment effects even under staggered adoption and heterogeneous responses and is shown by Baker et al. (2022) to be unbiased.

I implement stacked DiD estimation methods in Table 1.15, using yearly data of patent and citation counts over 3-year window surrounding the cross-border VC investments. There are mainly two steps of the estimations, constructing sample and DiD estimation.

First, I construct cohort-specific datasets for each treatment cohort, consisting of VC-PC pair investments from cross-border VCs (treatment group) and those from domestic VCs within a three-year window before and after the treatment year. Restricting the sample to these “clean” comparison observations ensures that units exposed to the treatment earlier are never used as controls for units treated later, and thereby yields unbiased results.

Second, I stack all the cohort-specific datasets and conduct DiD analysis on the stacked dataset. The outcome variables capturing firms’ innovation performance are measured by number of patents and number of citations, which are winsorized by 1st percentile and 99th percentile. In addition, following Hoepner et al. (2024), I incorporate country and investment year fixed effects interact with cohort, and add stage cohort fixed effects. Table 1.15 Panel A presents the estimation results.

[Table 1.15: Panel A: Stacked DiD Regression]

All positive and significant coefficients throughout columns in Panel A indicate that cross-border VC investments increase patent and citation counts significantly, in line with the previous findings. Column (1) and Column (2) present the result of OLS regressions, with the dependent variables of natural logarithm of one plus the number of patents and citations, respectively. The estimated coefficients are 0.193 at 10% significant level and 0.3632 at 5% significant level, illuminating that investee companies produce 21.3% more patents and 43.8% more citations than the control group.

Furthermore, I follow Farida et al. (2026) using poisson pseudo-maximum likelihood models to estimate the impact of cross-border VCs on innovation. The results are consistent with the main findings, shown as positive and significant estimated coefficients for patents and citations counts. A coefficient of 0.4971 in Column (3) indicates that treatment is associated with an approximately 64.4% more patents compared with the control group; the coefficient for citations is estimated as 1.0463 and significant at 1% level, indicating a significant proportional increase of 184.7% in expected citations when the investee companies are invested by cross-border VCs.

To establish the identification in DiD models, the parallel trends assumption must be satisfied, which requires that without the treatment effects, outcome difference for treated and control groups would be constant over time. In panel B of Table 1.15, I examine the dynamic outcomes of patents and citations in the 3 years before and after cross-border VC investments.

[Table 1.15: Panel B: Parallel Trend]

This dynamic analysis helps rule out the possibility that simultaneous, unobserved factors, rather than the treatment, cross-border VCs, itself, drive the estimated treatment effects. I use one period before the treatment as the reference point. The results indicate that before treatment, the estimated coefficients for T-3, and T-2 are insignificant through all columns, indicating that there is no significant difference of patents and citations counts between treated and control groups, and the parallel trends assumption holds. Furthermore, the OLS results in Column 1 and Possion regression results in Column (3) present that the number of patents increase significantly after 1 year of cross-border VC investments, and the increasing effect remains significant two and three years post the investments, with a reduced magnitude. Moreover, estimations in Column (2) and Column (4) show that the increasing effect on citations start in the investment year. The coefficients in Column (2) indicate that the effect last until 3 years after cross-border VC investments. The results align with Farida et al. (2026), who document a similar persistent effect on innovation outcomes. Therefore, the stacked DiD estimations suggest the robust findings, cross-border VCs increase innovation performance, as higher number of patents, and greater number of citations.

3.7.5 Subsample

To address concerns about firms that never file patents and the non-normal distribution of patents and citations, I construct a subsample to examine the relationship between cross-border VCs and innovation. Chemmanur et al. (2014) analyze firms with at least one patent before or after investment to assess the impact of CVC on innovation, while Tian and Wang (2014) use firm-year observations with positive patent counts to study VC syndication. Following these studies and considering the time required for the first patent grant, I select firms with at least one patent during the sample period. This subsample, which includes only firms with positive patent counts, reduces the sample size to 1,562 observations. Using the subsample, I apply Heckman's two-stage estimation to analyse the relationship between cross-border VCs and innovation performance using a three-year window in the second stage. The first stage employs a probit regression to estimate the likelihood of cross-border investment, while the second stage uses OLS regression to assess its impact on innovation outcomes, including patent counts, citations, and citations per patent. The results are presented in Table 1.16. Column (1) of Table 1.16 presents the first stage estimations, which is the same as the baseline results. Furthermore, results in Columns (2) - (4) demonstrate that the coefficients for all innovation measures remain positive and significant at the 1% level, indicating that cross-border VCs contribute to higher patent counts, citations, and citations per patent after investee firms secure their first patent. While the estimates are slightly higher than baseline results, they reinforce the greater impact of cross-border VCs on innovation. The control variable coefficients align with baseline findings, confirming that larger investment sizes enhance innovation. In addition, the coefficient for LnGDP is negative and significant.

[Table 1.16 subsample]

3.7.6 VC country innovation level and cross-border investment

To examine whether VCs from high or low innovation countries are more likely to engage in cross-border investments, I include the VC country innovation level variable (HGII_VC) in the first-stage analysis. High-innovation VC countries are defined as those in the top 25th percentile of the Global Innovation Index (GII), with HGII_VC assigned a value of one if the VC investor is from such a country and zero otherwise. The estimated results are reported in Table 1.17. Column (1) presents the first-stage estimations, consistent with previous findings, and confirming that larger syndication sizes, and greater investment amounts increase the likelihood of cross-border VC investments. In addition, the positive and significant coefficient for HGII_VC suggests that VCs from high-innovation countries are more inclined to invest across borders than those from low-innovation countries. Moreover, Columns (2) – (4) report second-stage estimates, which align with baseline results and show a greater impact of cross-border VCs on innovation, as reflected in both patents and citations count. However, the coefficient for citations per patent is not significant.

[Table 1.17 high innovation country]

3.7.7 High-Tech sectors and cross-border VC investment

I extend the Heckman two-stage model by incorporating a high-technology industry variable in both stages to assess the industry characteristics' impact on innovation. High-tech industries include Biotechnology, Communication, Computer-related, Medical, and Semiconductor/Electronics, represented by the dummy variable High_Tech, which equals one if the investee firm operates in these sectors and zero otherwise. I present the results in Table 1.18 below. These suggest that VCs are more inclined to engage in high-technology cross-border investments, as the coefficient for High_Tech in first stage (Column 1) is positive and significant at 1%. However, the estimated coefficients for High_Tech are not significant in second stage estimations, shown in Column (2)-(4), indicating the high-tech sector is not necessarily associate with greater innovation. The positive and significant coefficients for CBVC in Columns (2) - (4) confirm its impact on both innovation quantity and quality.

[Table 1.18 high tech industry]

3.8. Concluding Remarks

This study examines whether cross-border VCs have a greater impact on investee company innovation than domestic VCs. I use the unique expanded international patent and VC database and run the OLS regressions with year, industry, and stage fixed effect in baseline tests. The baseline results show that cross-border VCs make no difference in innovation than domestic VCs. However, the subsample of companies with positive patents count indicates a positive significant relationship between cross-border VCs and innovation. In addition, given VCs invest abroad due to the saturated domestic market and the pursuit of new business opportunities, I observe that most of the cross-border VC investments are made from high innovation countries. Therefore, I infer that cross-border VCs are more likely to invest in low innovation companies. Furthermore, the selection bias result in a downward bias in the outcomes. I utilize the Heckman two-stage approach to alleviate the downward bias. After separating the selection of cross-border VCs, my findings demonstrate a significant increase in the number of patents and citations for investee companies when cross-border VCs are involved. In addition, in the subsample of companies with positive patent count, it suggests that cross-border VCs increase innovation significantly more than domestics VCs. These results remain robust across various measuring windows. Hence, I infer that cross-border VCs tend to invest in low-innovation investee companies for the purpose of international diversification and high innovation potential. After the company generates patents, cross-border VCs notably enhance both the quantity and quality of innovation in their investee companies.

Furthermore, I conduct the supportive tests to elaborate that cross-border VCs utilize distinct risk management skills to investments, and they are more tolerance to investee companies. Specially, they stay longer and are more committed to the investee companies, and eventually boost their innovation. In addition, the evidence supports that cross-border VCs increase innovation through knowledge diffusion. Most of the cross-border VCs are initialled conducted by VCs from high innovation country and then the financial transactions build bridges for resources sharing and knowledge diffusion, then spurring innovation eventually.

3.9. Appendix

Appendix A: Variable Definitions:

Innovation Variables (Source: Orbis-IP)

PATENT: The number of patents that are applied and final granted for the investee company within the measuring window.

CITATION: The number of citations received from the patents which are applied and final granted after investments.

CIT/PATENT: The number of citations per patent, calculated by the number of citation divided by the number of patents.

LnPATENT: The natural logarithm of 1 plus the total number of patents granted to each investee company within the measuring window.

LnCITATION: The natural logarithm of 1 plus the total number of citations received on each company's patents within the measuring window.

LnCIT/PATENT: The natural logarithm of 1 plus the total number of citations per patent for each investee company within the measuring window.

VC Ownership and Characteristic Variables (Source: Refinitiv Eikon)

CBVC: A dummy variable, when Investee Company Nation is different from Firm Investors Nation, the dummy variable equals one, otherwise zero.

Perc_CBVC: Calculated by dividing the number of cross-border VCs to the number of VCs in the investment year.

NumVCs: The number of VCs involved in the investment

LnVCAge: Natural logarithm of one plus the difference between the investment year and the VC's founding year.

LnFUNDAge: Natural logarithm of one plus the difference between fund founded year and investment year.

LnINVSize: Natural logarithm of one plus the round equity.

DevStage: A categorical variable including Startup/Seed, Early Stage, Expansion, Later Stage, and Buyout/Acquisition.

Average period: simple average duration of all failed investments in a VC's investment history.

Weighted average period: the investment-size-weighted average duration of all failed investments in a VC's investment history.

Maximum period: the longest duration of all failed investments in a VC's investment history.

Country-level Innovativeness and Country Characteristic (Source: World Bank, World Development Indicators (WDI), and other sources)

Ln GDP: The natural logarithm of the country GDP per capita.

MARKETDev: The natural logarithm of one plus the country stock market capitalization divided by country GDP.

Ln_inflow: The natural logarithm of one plus the capital inflow into the VC industry in home country.

hgii_p25_vc: A categorical variable for a country's innovation level, including high, medium, and low. Countries are categorized by innovation levels measured by GII index. High-innovation countries have an index above the 75th percentile, medium-innovation countries fall within the 25th to 75th percentile, and low-innovation countries are below the 25th percentile.

High_Tech: A dummy variable, when investee companies are in Biotechnology, communication, Computer related, Medical, and Semiconductor/Electric, the dummy variable equals one, otherwise zero.

Appendix B: Tables

Table 1.1: Descriptive statistics

Panel A: VC ownership

CBVC	Freq.	Percent	Cum.
0	8,965	82.672	82.672
1	1,879	17.328	100.000
Total	10,844	100.000	

Panel B: Patent Variables	N	Mean	SD	Min	Max
PATENT_3y	10,844	2.736	35.748	0.000	2860.000
CITATION_3y	10,844	18.392	199.583	0.000	10260.000
CIT/PATENT_3y	10,844	1.443	12.239	0.000	557.000
LnPATENT _3y	10,844	0.289	0.825	0.000	7.959
LnCITATION _3y	10,844	0.508	1.331	0.000	9.236
LnCIT/PATENT _3y	10,844	0.215	0.678	0.000	6.324
PATENT_5y	10,844	4.757	59.665	0.000	3988.000
CITATION_5y	10,844	28.181	291.644	0.000	13936.000
CIT/PATENT_5y	10,844	1.600	14.374	0.000	674.000
LnPATENT _5y	10,844	0.361	0.963	0.000	8.291
LnCITATION _5y	10,844	0.600	1.470	0.000	9.542
LnCIT/PATENT _5y	10,844	0.241	0.705	0.000	6.515

Panel C: Patent Variables means by groups

	Domestic VC		Cross-border VC			
	N	Mean	N	Mean	MeanDiff	p-Value
PATENT_3y	8,965	2.293	1,879	4.849	-2.556	0.005***
CITATION_3y	8,965	16.326	1,879	28.250	-11.924	0.019**
CIT/PATENT_3y	8,965	1.405	1,879	1.621	-0.216	0.488
LnPATENT _3y	8,965	0.293	1,879	0.27	0.022	0.284
LnCITATION _3y	8,965	0.511	1,879	0.491	0.02	0.558
LnCIT/PATENT _3y	8,965	0.217	1,879	0.204	0.014	0.424
PATENT_5y	8,965	4.318	1,879	6.854	-2.536	0.094*
CITATION_5y	8,965	25.235	1,879	42.239	-17.005	0.022**
CIT/PATENT_5y	8,965	1.527	1,879	1.949	-0.421	0.248
LnPATENT _5y	8,965	0.365	1,879	0.337	0.029	0.241
LnCITATION _5y	8,965	0.605	1,879	0.577	0.027	0.466
LnCIT/PATENT _5y	8,965	0.246	1,879	0.218	0.029	0.108

Panel D: Control variables	N	Mean	SD	Min	Max
VCAGE	10,844	14.127	15.898	0.000	182
FundAGE	10,844	9.633	14.185	0.000	133
INVSize	10,844	2.438	9.97	0.000	343.16
LnVCAge	10,844	2.203	1.074	0.000	5.209
LnFUNDAge	10,844	1.674	1.155	0.000	4.898
LnINVSize	10,844	0.592	0.858	0.000	5.841
WDI_GDP_Investee (Millions)	10,844	5,320,000	5,820,000	4,160	18,200,000
LnGDP	10,844	9.977	1.085	5.994	11.687
MARKETDev	10,844	0.949	0.736	0.000	12.545

Panel E: stage of investee company development when received VC investment

Deal Round Financing Stage	Freq.	Percent	Cum.
Startup/Seed	1,574	14.515	14.515
Early Stage	3,584	33.051	47.565
Expansion	3,490	32.184	79.749
Later Stage	1,298	11.970	91.719
Buyout/Acquisition	898	8.281	100
Total	10,844	100.000	

Table 1.2: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) LnPATENTS_3y	1.000													
(2) LnPATENTS_5y	0.963	1.000												
	(0.000)													
(3) LnCITATIO_3y	0.832	0.813	1.000											
	(0.000)	(0.000)												
(4) LnCITATIO_5y	0.820	0.850	0.959	1.000										
	(0.000)	(0.000)	(0.000)											
(5) LnCIT/Patent_3y	0.055	0.672	0.836	0.800	1.000									
	0.029	0.000	0.000	0.000										
(6) LnCIT/Patent_5y	0.029	0.671	0.785	0.831	0.913	1.000								
	0.261	0.000	0.000	0.000	0.000									
(7) CBVC	-0.010	-0.011	-0.006	-0.007	-0.006	-0.007	1.000							
	(0.284)	(0.241)	(0.558)	(0.466)	0.558	0.466								
(8) Perc_CBVC	-0.018	-0.020	-0.012	-0.013	-0.012	-0.013	0.996	1.000						
	(0.057)	(0.040)	(0.214)	(0.172)	0.214	0.172	(0.000)							
(9) NumVCs	0.244	0.254	0.227	0.226	0.227	0.226	-0.004	-0.038	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	0.690	(0.000)						
(10) LnVCAge	0.005	0.004	-0.011	-0.015	-0.011	-0.015	0.056	0.054	0.047	1.000				
	(0.585)	(0.711)	(0.251)	(0.113)	0.251	0.113	(0.000)	(0.000)	(0.000)					
(11) LnFUNDAge	-0.004	-0.005	-0.020	-0.025	-0.020	-0.025	0.013	0.012	0.050	0.701	1.000			
	(0.644)	(0.571)	(0.036)	(0.010	0.036	0.010	(0.185)	(0.207)	(0.000)	(0.000)				
(12) LnINVSize	0.105	0.112	0.101	0.102	0.101	0.102	0.105	0.099	0.177	0.042	-0.006	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	0.549			
(13) LnGDP	-0.104	-0.113	-0.061	-0.067	-0.061	-0.067	-0.153	-0.150	-0.101	0.100	0.118	-0.125	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(14) MARKETDev	-0.089	-0.095	-0.052	-0.058	-0.052	-0.058	0.074	0.077	-0.032	0.039	0.053	0.083	0.250	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 1.3: Summary statistics _ subsample

Panel A: Summary statistics

Variable	N	Mean	SD	Min	Max
LnPATENT	1,562	2.065	1.207	0.693	8.063
LnCITATION	1,562	3.020	1.978	0.000	11.239
LnCIT/PATENT	1,562	1.512	1.140	0.000	6.324
CBVC	1,562	0.153	0.360	0.000	1.000
NumCBVC	1,562	0.155	0.366	0.000	2.000
Perc_CBVC	1,562	0.144	0.346	0.000	1.000
LnVCAge	1,562	2.314	1.063	0.000	4.970
LnFUNDAge	1,562	1.749	1.212	0.000	4.875
LnINVSize	1,562	0.749	0.980	0.000	5.311
DecStage	1,562	3.528	1.619	1.000	7.000
LnGDP	1,562	9.788	1.068	5.990	11.548
MARKETDev	1,562	0.810	0.493	0.074	11.093
NumVCs	1,562	1.242	0.851	1.000	7.000
Industry	1,562	9.839	4.645	1.000	18.000
investmentyear	1,562	2,006.788	5.514	1,996.000	2,015.000
country_id_investee	1,562	148.474	83.267	16.000	251.000

Panel B: patent variables summary statistics

Variable	N	Mean	SD	Min	Max
PATENT_3y	1,562	26.043	137.620	1.000	3,174.000
LnPATENT _3y	1,562	2.065	1.207	0.693	8.063
PATENT _5y	1,562	44.623	229.617	1.000	5,810.000
Ln PATENT _5y	1,562	2.401	1.348	0.693	8.668
CITATION_3y	1,562	251.364	2395.107	0.000	76064.000
LnCITATION _3y	1,562	3.020	1.978	0.000	11.239
CITATION_5y	1,562	386.647	3605.501	0.000	96434.000
LnCITATION _5y	1,562	3.394	2.032	0.000	11.477
CIT/PATENT_3y	1,562	10.370	32.008	0.000	557.000
LnCIT/PATENT_3y	1,562	1.512	1.140	0.000	6.324
CIT/PATENT_5y	1,562	9.646	28.547	0.000	402.000
LnCIT/PATENT_5y	1,562	1.524	1.082	0.000	5.999

Panel C: t-test for all variables

	Domestic VCs		Cross-border VC			
Variables	N	Mean	N	Mean	MeanDiff	p-Value
LnPATENT _3y	1,256	2.014	306	2.345	-0.331	0.000***
LnCITATION _3y	1,256	2.945	306	3.435	-0.490	0.000***
LnCIT/PATENT _3y	1,256	1.491	306	1.627	-0.136	0.054*
Num_CBVC	1,256	0.000	306	1.01	-1.01	0.000***
NumVCs	1,256	1.240	306	1.255	-0.015	0.777
InvesteeCompanyAGE	1,256	10.06	306	10.727	-0.668	0.515
LnVCAge	1,256	2.284	306	2.475	-0.191	0.004***
LnFUNDAge	1,256	1.759	306	1.694	0.065	0.387
LnInvSize	1,256	0.708	306	0.976	-0.268	0.000***
DevStage	1,256	3.570	306	3.29	0.283	0.005***
LnGDP	1,256	9.790	306	9.750	0.0470	0.509
MARKETDev	1,256	0.805	306	0.837	-0.031	0.346

Panel D: subsample_correlation matrix:

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) LnPATENT _3y	1.000													
(2) LnPATENT_5y	0.964	1.000												
(3) LnCITATION_3y	0.706	0.688	1.000											
(4) LnCITATION_5y	0.698	0.740	0.951	1.000										
(5) CBVC	-0.013	-0.014	-0.016	-0.019	1.000									
(6) NumCBVC	-0.011	-0.013	-0.014	-0.017	0.998	1.000								
(7) Perc_CBVC	-0.022	-0.024	-0.023	-0.026	0.995	0.992	1.000							
(8) NumVCs	0.248	0.258	0.222	0.231	0.003	0.010	-0.036	1.000						
(9) LnVCAge	0.023	0.023	0.020	0.017	0.031	0.031	0.028	0.054	1.000					
(10) LnFUNDAge	0.010	0.010	0.006	0.004	-0.014	-0.014	-0.015	0.047	0.714	1.000				
(11) LnInvSize	0.097	0.103	0.090	0.090	0.100	0.100	0.093	0.161	0.068	0.026	1.000			
(12) DevStage	0.036	0.037	0.052	0.053	-0.058	-0.057	-0.058	0.021	-0.007	-0.020	-0.025	1.000		
(13) LnGDP	-0.095	-0.107	-0.025	-0.031	-0.161	-0.160	-0.158	-0.086	0.071	0.080	-0.144	0.028	1.000	
(14) MARKETDev	-0.082	-0.088	-0.050	-0.057	0.051	0.051	0.054	-0.031	0.049	0.057	0.056	-0.011	0.245	1.000

Table 1.4: OLS regression

Panel A: Dummy variable of Cross-border VC as main explanation variable

The table presents results of the OLS regressions. The dependent variables are natural logarithm transformed number of patents, citations, and citations per patent, respectively. The independent variables are dummy variable of cross-border VCs in Panel A, and percentage of cross-border VCs in Panel B, number of VCs, natural logarithm transformed VC age, natural logarithm transformed fund age, natural logarithm transformed investment size, natural investment stage, natural logarithm transformed investee country GDP, and investee company country Equity. Heteroskedasticity-robust standard errors clustered by investee companies are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	LnPATENT		LnCITATION		LnCIT/PATENT	
3-year window	(1)	(2)	(3)	(4)	(5)	(6)
CBVC	0.019	0.015	0.028	0.021	0.007	0.008
	(0.023)	(0.023)	(0.035)	(0.036)	(0.017)	(0.018)
NumVCs		0.373***		0.573***		0.222***
		(0.065)		(0.095)		(0.045)
LnVCAge		0.003		-0.004		-0.005
		(0.010)		(0.016)		(0.008)
LnFUNDAge		-0.009		-0.027*		-0.010
		(0.009)		(0.015)		(0.007)
LnInvSize		0.042***		0.064***		0.021**
		(0.011)		(0.016)		(0.008)
LnGDP		0.006		0.065		-0.010
		(0.056)		(0.082)		(0.037)
MARKETDev		-0.001		0.015		0.002
		(0.011)		(0.021)		(0.011)
_cons	0.299***	-0.197	0.520***	-0.786	0.220***	0.083
	(0.008)	(0.551)	(0.013)	(0.801)	(0.007)	(0.368)
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes	Yes	Yes
N	10,844	10,844	10,844	10,844	10,844	10,844
R-sq	0.180	0.207	0.152	0.178	0.104	0.120
adj. R-sq	0.172	0.200	0.144	0.170	0.095	0.112

Panel B: Percentage of Cross-border VC as main explanation variable

	LnPATENT		LnCITATION		LnCIT/PATENT	
3-year window	(1)	(2)	(3)	(4)	(5)	(6)
Perc_CBVC	0.006	0.018	0.010	0.027	0.001	0.011
	(0.021)	(0.022)	(0.033)	(0.035)	(0.016)	(0.018)
NumVCs		0.373***		0.574***		0.222***
		(0.065)		(0.095)		(0.045)
LnVCAge		0.003		-0.004		-0.005
		(0.010)		(0.016)		(0.008)
LnFUNDAge		-0.009		-0.026*		-0.010
		(0.009)		(0.015)		(0.007)
LnInvSize		0.042***		0.063***		0.021**
		(0.011)		(0.016)		(0.008)
LnGDP		0.006		0.065		-0.010
		(0.056)		(0.082)		(0.037)
MARKETDev		-0.001		0.015		0.002
		(0.011)		(0.021)		(0.011)
_cons	0.302***	-0.198	0.523***	-0.787	0.222***	0.083
	(0.008)	(0.552)	(0.013)	(0.801)	(0.007)	(0.368)
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes	Yes	Yes
N	10,844	10,844	10,844	10,844	10,844	10,844
R-sq	0.180	0.207	0.152	0.178	0.104	0.120
adj. R-sq	0.172	0.200	0.144	0.170	0.095	0.112

Table 1.5: Different windows

The table presents results of the OLS regressions. The dependent variables are natural logarithm transformed number of patents, citations, and citations per patent, respectively. The independent variables are dummy variable of cross-border VCs in column 1 to column 6, and percentage of cross-border VCs in column 7 to column 12, number of VCs, natural logarithm transformed VC age, natural logarithm transformed fund age, natural logarithm transformed investment size, natural investment stage, natural logarithm transformed investee country GDP, and investee company country Equity. The dependent variables in Panel A are measured with the 5-year window, and 10-year window in Panel B. Heteroskedasticity-robust standard errors clustered by investee companies are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: 5-year window

	LnPATENT		LnCITATION		LnCIT/PATENT		LnPATENT		LnCITATION		LnCIT/PATENT	
5-year window	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CBVC	0.017	0.014	0.020	0.022	-0.010	-0.004						
	(0.026)	(0.026)	(0.038)	(0.040)	(0.017)	(0.019)						
Perc_CBVC						0	0.001	0.017	0.002	0.030	-0.015	0.001
							(0.024)	(0.025)	(0.036)	(0.038)	(0.017)	(0.018)
NumVCs		0.442***		0.614***		0.218***		0.443***		0.615***		0.218***
		(0.074)		(0.102)		(0.042)		(0.074)		(0.102)		(0.042)
LnVCAge		0.001		-0.011		-0.012		0.001		-0.011		-0.012
		(0.011)		(0.017)		(0.009)		(0.011)		(0.017)		(0.009)
LnFUNDAge		-0.007		-0.028*		-0.009		-0.007		-0.028*		-0.009
		(0.010)		(0.016)		(0.007)		(0.010)		(0.016)		(0.007)
LnInvSize		0.051***		0.064***		0.020**		0.051***		0.064***		0.020**
		(0.012)		(0.018)		(0.008)		(0.012)		(0.018)		(0.008)
LnGDP		-0.033		0.004		-0.030		-0.033		0.004		-0.030
		(0.065)		(0.091)		(0.038)		(0.065)		(0.091)		(0.038)
MARKETDev		0.002		0.019		-0.000		0.002		0.019		-0.000
		(0.013)		(0.024)		(0.011)		(0.013)		(0.024)		(0.011)
_cons	0.375***	0.177	0.619***	-0.113	0.251***	0.336	0.378***	0.176	0.622***	-0.114	0.252***	0.337
	(0.009)	(0.642)	(0.014)	(0.895)	(0.007)	(0.378)	(0.010)	(0.642)	(0.014)	(0.895)	(0.007)	(0.378)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10,844	10,844	10,844	10,844	10,844	10,844	10,844	10,844	10,844	10,844	10,844	10,844
R-sq	0.206	0.233	0.175	0.196	0.114	0.126	0.206	0.233	0.175	0.196	0.114	0.126
adj. R-sq	0.198	0.227	0.166	0.188	0.105	0.118	0.198	0.227	0.166	0.188	0.105	0.118

Table 1.6: Subsample baseline

The table presents results of the OLS regressions for subsample of investee companies with positive patent count. The dependent variables are natural logarithm transformed number of patents, citations, and citations per patent, respectively. The independent variables are dummy variable of cross-border VCs in Panel A, and percentage of cross-border VCs in Panel B, number of VCs, natural logarithm transformed VC age, natural logarithm transformed fund age, natural logarithm transformed investment size, natural investment stage, natural logarithm transformed investee country GDP, and investee company country Equity. Heteroskedasticity-robust standard errors clustered by investee companies are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: dummy variable cbvc

	LnPATENT		LnCITATION		LnCIT/PATENT	
3-year window	(1)	(2)	(3)	(4)	(5)	(6)
CBVC	0.284***	0.223**	0.420***	0.309**	0.122*	0.094
	(0.094)	(0.101)	(0.142)	(0.154)	(0.073)	(0.081)
NumVCs		0.050		0.131		0.047
		(0.043)		(0.094)		(0.052)
LnVCAge		0.032		0.022		-0.000
		(0.036)		(0.061)		(0.036)
LnFUNDAge		0.030		-0.017		-0.046
		(0.032)		(0.054)		(0.031)
LnInvSize		0.135***		0.164***		0.013
		(0.036)		(0.054)		(0.031)
LnGDP		0.239		0.482*		0.219*
		(0.187)		(0.265)		(0.130)
MARKETDev		0.122		0.368*		0.216**
		(0.116)		(0.199)		(0.109)
_cons	2.025***	-0.779	2.961***	-2.514	1.494***	-0.838
	(0.030)	(1.840)	(0.049)	(2.613)	(0.027)	(1.285)
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes	Yes	Yes
N	1,562	1,562	1,562	1,562	1,562	1,562
R-sq	0.125	0.159	0.150	0.184	0.211	0.233
adj. R-sq	0.093	0.123	0.120	0.149	0.183	0.200

Panel B: percentage of cbvc as main explanation variable

	LnPATENT		LnCITATION		LnCIT/PATENT	
3-year window	(1)	(2)	(3)	(4)	(5)	(6)
Perc_CBVC	0.287***	0.258**	0.441***	0.383**	0.140*	0.124
	(0.098)	(0.105)	(0.146)	(0.156)	(0.076)	(0.083)
NumVCs		0.059		0.143		0.051
		(0.042)		(0.092)		(0.052)
LnVCAge		0.030		0.020		-0.001
		(0.036)		(0.061)		(0.036)
LnFUNDAge		0.032		-0.014		-0.045
		(0.032)		(0.054)		(0.031)
LnInvSize		0.136***		0.163***		0.012
		(0.036)		(0.054)		(0.031)
LnGDP		0.240		0.484*		0.219*
		(0.186)		(0.264)		(0.130)
MARKETDev		0.122		0.370*		0.217**
		(0.116)		(0.198)		(0.109)
_cons	2.027***	-0.806	2.961***	-2.551	1.493***	-0.850
	(0.030)	(1.837)	(0.049)	(2.608)	(0.027)	(1.284)
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes	Yes	Yes
N	1,562	1,562	1,562	1,562	1,562	1,562
R-sq	0.124	0.160	0.150	0.185	0.212	0.233
adj. R-sq	0.093	0.124	0.120	0.150	0.183	0.201

Table 1.7: Different window: 5-year window

The table presents results of the OLS regressions for subsample of investee companies with positive patent count. The dependent variables are natural logarithm transformed number of patents, citations, and citations per patent, respectively. The independent variables are dummy variable of cross-border VCs in column 1 to column 6, and percentage of cross-border VCs in column 7 to column 12, number of VCs, natural logarithm transformed VC age, natural logarithm transformed fund age, natural logarithm transformed investment size, natural investment stage, natural logarithm transformed investee country GDP, and investee company country Equity. The dependent variables in Panel A are measured with the 5-year window, and 10-year window in Panel B. Heteroskedasticity-robust standard errors clustered by investee companies are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	LnPATENT		LnCITATION		LnCIT/PATENT		LnPATENT		LnCITATION		LnCIT/PATENT	
5-year window	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CBVC	0.322***	0.268**	0.385***	0.300*	0.064	0.044						
	(0.096)	(0.105)	(0.142)	(0.155)	(0.068)	(0.075)						
Perc_CBVC							0.322***	0.311***	0.423***	0.397**	0.095	0.086
							(0.103)	(0.110)	(0.146)	(0.155)	(0.070)	(0.076)
NumVCs		0.0765*		0.126		0.027		0.0871*		0.139		0.030
		(0.046)		(0.095)		(0.049)		(0.045)		(0.093)		(0.048)
LnVCAge		0.034		0.019		-0.008		0.032		0.015		-0.009
		(0.039)		(0.062)		(0.034)		(0.039)		(0.062)		(0.034)
LnFUNDAge		0.037		-0.012		-0.047		0.039		-0.008		-0.045
		(0.035)		(0.056)		(0.029)		(0.035)		(0.056)		(0.029)
LnInvSize		0.149***		0.152***		-0.001		0.149***		0.151***		-0.002
		(0.037)		(0.054)		(0.029)		(0.037)		(0.054)		(0.029)
LnGDP		0.083		0.151		0.099		0.085		0.152		0.099
		(0.200)		(0.269)		(0.120)		(0.199)		(0.268)		(0.120)
MARKETDev		0.212*		0.453**		0.191*		0.212*		0.456**		0.193*
		(0.124)		(0.200)		(0.107)		(0.124		(0.200)		(0.108)
_cons	2.357***	0.897	3.341***	1.015	1.515***	0.427	2.360***	0.865	3.340***	0.978	1.511***	0.421
	(0.033)	(1.966)	(0.050)	(2.646)	(0.025)	(1.190)	(0.033)	(1.963)	(0.050)	(2.641)	(0.025)	(1.189)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,990	1,802	1,990	1,802	1,990	1,802	1,990	1,802	1,990	1,802	1,990	1,802
R-sq	0.165	0.203	0.186	0.218	0.241	0.262	0.165	0.204	0.186	0.220	0.242	0.262
adj. R-sq	0.135	0.169	0.156	0.185	0.214	0.230	0.134	0.170	0.157	0.186	0.214	0.230

Table 1.8: IV & Heckman Two Stage Estimations (3-year window)

This table presents the results of Heckman Two Stage estimations using 3-year window. The first column shows the first stage results, and the following two columns present the second stage results. The dependent variables are natural logarithm of the number of patents and the number of citations, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses. LR chi2 is reported for the first stage probit estimation.

	First Stage	LnPATENT	LnCITATION	LnCIT/PATENT
3-year window	(1)	(2)	(3)	(4)
CBVC		0.269***	0.427***	0.117
		(0.079)	(0.107)	(0.075)
NumVCs	0.574***	0.061	0.238**	-0.008
	(0.048)	(0.078)	(0.108)	(0.077)
LnVCAge	-0.025	0.009	-0.047	-0.030
	(0.021)	(0.035)	(0.049)	(0.035)
LnFUNDAge	-0.037*	0.027	0.004	0.013
	(0.020)	(0.033)	(0.046)	(0.032)
LnINVSize	0.061***	0.135***	0.191***	0.042
	(0.019)	(0.035)	(0.050)	(0.035)
LnGDP	-0.008	-0.122***	-0.065	0.074**
	(0.017)	(0.033)	(0.045)	(0.033)
MARKETDev	-0.380***	-0.104	0.138	0.474***
	(0.043)	(0.107)	(0.093)	(0.100)
Ln_infow	0.021***			
	(0.007)			
_cons	-1.489***	2.905***	3.200***	1.833***
	(0.266)	(0.668)	(0.921)	(0.604)
lambda		0.017	0.390	-0.153
		(0.283)	(0.375)	(0.289)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes
Wald chi2/LR chi2	1529.88***	181.32***	177.17***	271.56
N	10,844	10,844	10,844	10,844

Table 1.9: Test for tolerance for failure

This table represents two sample t-tests of the time VCs stayed with investee companies that ended up with a failure for domestic and cross-border VCs.

Variables	Domestic VC (1)	Mean1	Cross-border VC (2)	Mean2	MeanDiff
Average period	8,965	0.721	1,879	0.796	-0.075***
Weighted average period	9,791	0.866	2,074	1.083	-0.217***
Maximum period	9,791	3.307	2,074	4.18	-0.874***

Table 1.10: Distribution for knowledge diffusion

This table displays the distribution of investment flow between nations depending on their level of innovation. Global Innovation Index (GII) is used to categorize the innovation level of investor and investee nations. High innovation countries are the ones above the 25th percentile, medium innovation countries are the ones between the 25th and 75th percentiles, and low innovation countries are the ones below the 75th percentile.

Flow	Domestic investments	Cross-border investments	Total
1 high to high	810	30	840
2 high to medium	0	155	155
3 high to low	0	70	70
4 medium to high	0	165	165
5 medium to medium	5,381	568	5,949
6 medium to low	0	576	576
7 low to high	0	34	34
8 low to medium	0	153	153
9 Low to low	2,774	128	2,902
Total	8,965	1,879	10,844

Table 1.11: IV & Heckman Two Stage Estimations (5-year window)

This table presents the results of Heckman Two Stage estimations using 5-year window. The first column shows the first stage results, and the following two columns present the second stage results. The dependent variables are natural logarithm of the number of patents, the number of citations, and the number of citations per patent, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses. LR chi2 is reported for the first stage probit estimation.

	First Stage	LnPATENT	LnCITATION	LnCIT/PATENT
5-year window	(1)	(2)	(3)	(4)
CBVC		0.309***	0.376***	0.065
		(0.081)	(0.105)	(0.069)
NumVCs	0.635***	0.160**	0.250**	-0.005
	(0.051)	(0.076)	(0.107)	(0.065)
LnVCAge	-0.036*	0.022	-0.038	-0.039
	(0.021)	(0.037)	(0.048)	(0.032)
LnFUNDAge	-0.030	0.021	0.018	0.017
	(0.019)	(0.034)	(0.045)	(0.029)
LnINVSize	0.076***	0.138***	0.182***	0.038
	(0.019)	(0.036)	(0.050)	(0.031)
LnGDP	0.003	-0.204***	-0.135***	0.079***
	(0.016)	(0.034)	(0.044)	(0.029)
MARKETDev	-0.404***	-0.125	0.201**	0.493***
	(0.042)	(0.105)	(0.098)	(0.087)
Ln_inflow	0.021***			
	(0.007)			
_cons	-1.481***	3.454***	4.210***	1.497***
	(0.257)	(0.639)	(0.896)	(0.516)
lambda		0.234	0.244	-0.104
		(0.255)	(0.384)	(0.224)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes
Wald chi2/LR chi2	1632.68***	240.95***	216.06***	337.93***
N	10,844	10,844	10,844	10,844

Table 1.12: IV & Heckman (percentage-CBVC)

This table presents the results of Heckman Two Stage estimations using 3-year window. The first column shows the first stage results, and the following two columns present the second stage results. The dependent variables are natural logarithm of the number of patents, the number of citations, and the number of citations per patent, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses. LR chi2 is reported for the first stage probit estimation.

	First Stage	LnPATENT	LnCITATION	LnCIT/PATENT
3-year window	(1)	(2)	(3)	(4)
Perc_CBVC		0.287***	0.479***	0.165**
		(0.082)	(0.111)	(0.078)
NumVCs	0.574***	0.058	0.237**	-0.012
	(0.048)	(0.078)	(0.108)	(0.077)
LnVCAge	-0.025	0.009	-0.048	-0.031
	(0.021)	(0.035)	(0.049)	(0.035)
LnFUNDAge	-0.037*	0.028	0.007	0.014
	(0.020)	(0.033)	(0.046)	(0.032)
LnINVSize	0.061***	0.133***	0.188***	0.039
	(0.019)	(0.035)	(0.050)	(0.035)
LnGDP	-0.008	-0.121***	-0.063	0.076**
	(0.017)	(0.033)	(0.045)	(0.033)
MARKETDev	-0.380***	-0.090	0.144	0.483***
	(0.043)	(0.107)	(0.093)	(0.101)
Ln_inflow	0.021***			
	(0.007)			
_cons	-1.489***	2.964***	3.257***	1.858***
	(0.266)	(0.667)	(0.918)	(0.604)
lambda		0.132	0.389	-0.146
		(0.276)	(0.368)	(0.280)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes
Wald chi2/LR chi2	1529.88***	181.99***	180.97***	273.16***
N	10,844	10,844	10,844	10,844

Table 1.13: Poisson regression

This table reports Poisson regression results. The dependent variables are the number of patents, the number of citations, and the number of citations per patent respectively. The independent variables are dummy variable of cross-border VCs in columns 1 and 2, and percentage of cross-border VCs in columns 3 and 4. Control variables are the number of VCs, natural logarithm of VC age, natural logarithm of fund age, natural logarithm of investment size, natural investment stage, natural logarithm of investee country GDP, and investee company country Equity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

	PATENTS	CITATIONS	CIT/PATNET	PATENTS	CITATIONS	CIT/PATNET
3-year window	(1)	(2)	(3)	(4)	(5)	(6)
CBVC	0.721***	0.588***	0.268***			
	(0.013)	(0.005)	(0.021)			
Perc_CBVC				0.749***	0.608***	0.282***
				(0.014)	(0.005)	(0.021)
NumVCs	0.169***	0.195***	0.214***	0.191***	0.208***	0.221***
	(0.007)	(0.003)	(0.012)	(0.007)	(0.003)	(0.012)
LnVCAge	0.070***	0.010***	-0.106***	0.071***	0.009***	-0.106***
	(0.008)	(0.003)	(0.010)	(0.008)	(0.003)	(0.010)
LnFUNDAge	0.008	-0.033***	-0.034***	0.005	-0.033***	-0.034***
	(0.007)	(0.003)	(0.010)	(0.007)	(0.003)	(0.010)
LnINVSize	0.234***	0.302***	0.219***	0.235***	0.302***	0.220***
	(0.006)	(0.002)	(0.009)	(0.006)	(0.002)	(0.009)
LnGDP	-0.050***	0.031***	0.148***	-0.046***	0.033***	0.148***
	(0.005)	(0.002)	(0.010)	(0.005)	(0.002)	(0.010)
MARKETDev	-0.987***	-0.206***	0.073***	-0.995***	-0.209***	0.072***
	(0.017)	(0.005)	(0.011)	(0.017)	(0.005)	(0.011)
_cons	0.807***	2.943***	-0.851***	0.728***	2.901***	-0.870***
	(0.094)	(0.035)	(0.159)	(0.094)	(0.035)	(0.159)
Stage	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
LR Chi2	35,738.26	24,8907.72	15,096.57	35,831.90	249,370.89	15108.34
P value	0.000	0.000	0.000	0.000	0.000	0.000
N	10,844	10,844	10,844	10,844	10,844	10,844

Table 1.14: Negative Binomial Regression

This table reports Negative binomial regression results. The dependent variables are the number of patents, the number of citations, and the number of citations per patent respectively. The independent variables are dummy variable of cross-border VCs in columns 1 and 2, and percentage of cross-border VCs in columns 3 and 4. Control variables are the number of VCs, natural logarithm of VC age, natural logarithm of fund age, natural logarithm of investment size, natural investment stage, natural logarithm of investee country GDP, and investee company country Equity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

	PATENTS	CITATIONS	CIT/PATNET	PATENTS	CITATIONS	CIT/PATNET
3-year window	(1)	(2)	(3)	(4)	(5)	(6)
CBVC	1.094***	0.806***	-0.016			
	(0.154)	(0.174)	(0.142)			
Perc_CBVC				1.105***	0.823***	-0.009
				(0.155)	(0.175)	(0.143)
NumVCs	0.479***	0.383**	0.317**	0.524***	0.399**	0.317**
	(0.154)	(0.185)	(0.149)	(0.154)	(0.184)	(0.149)
LnVCAge	0.134**	0.137*	-0.120*	0.133**	0.135*	-0.120*
	(0.067)	(0.081)	(0.065)	(0.067)	(0.081)	(0.065)
LnFUNDAge	0.017	-0.042	0.033	0.016	-0.041	0.033
	(0.063)	(0.080)	(0.064)	(0.063)	(0.080)	(0.064)
LnINVSize	0.208***	0.331***	0.295***	0.207***	0.332***	0.295***
	(0.054)	(0.066)	(0.056)	(0.054)	(0.066)	(0.056)
LnGDP	0.479***	0.383**	0.108*	0.524***	0.399**	0.109*
	(0.154)	(0.185)	(0.058)	(0.154)	(0.184)	(0.058)
MARKETDev	0.134**	0.137*	-0.012	0.133**	0.135*	-0.012
	(0.067)	(0.081)	(0.094)	(0.067)	(0.081)	(0.094)
_cons	2.188**	3.305***	-0.046	2.115**	3.272***	-0.053
	(0.884)	(1.145)	(0.864)	(0.882)	(1.145)	(0.865)
Stage	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
LR Chi2	785.342	428.680	462.360	785.288	429.370	462.352
P value	0.000	0.000	0.000	0.000	0.000	0.000
N	10,844	10,844	10,844	10,844	10,844	10,844

Table 1.15: Stacked Difference-in-Differences

The table presents results of the stacked Difference-in-Differences regressions. The dependent variables are the natural logarithm of number of patents, citations, number of patents, and number of citations, respectively. The sample includes all investments from 1996 to 2017. Panel A presents the regression results. The independent variable is "CBVC", a dummy variable that equals one if an investee companies received cross-border VC investment within 3 years before the patent application. Panel B presents the dynamic effects from 3 years before until 3 years after the cross-border VCs investments. In both panels, Columns 1 and 2 use OLS regressions, whereas Column 3 and 4 use Poisson regressions. Heteroskedasticity-robust standard errors clustered by investee companies are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: regression results

	(1)OLS	(2)OLS	(3)Poisson	(4)Poisson
	LnPATENT	LnCITATION	PATENT	CITATION
CBVC	0.1930*	0.3632**	0.4971*	1.0463***
	(0.1034)	(0.1732)	(0.2843)	(0.2699)
Year x cohort	Yes	Yes	Yes	Yes
Stage x cohort	Yes	Yes	Yes	Yes
Country x cohort	Yes	Yes	Yes	Yes
_cons	1.2440***	1.3410***	2.4882***	3.6829***
	(0.0295)	(0.0420)	(0.0900)	(0.1293)
N	53,666	39,778	53,666	39,778
R-sq/ Wald Chi2	0.161	0.177	3.06	15.03
adj. R-sq/ Pseudo R2	0.147	0.160	0.243	0.364

Panel B: Parallel trend

	(1)	(2)	(3)	(4)
	LnPATENT	LnCITATION	PATENT	CITATION
t-3	0.0001	-0.0001	0.0001	0.0006
	(0.0004)	(0.0007)	(0.0015)	(0.0018)
t-2	0.0002	-0.0000	0.0003	-0.0002
	(0.0003)	(0.0005)	(0.0009)	(0.0017)
treat	0.0004	0.0058*	0.0056	0.0155*
	(0.0019)	(0.0033)	(0.0054)	(0.0091)
T+1	0.0054***	0.0058**	0.0094*	0.0081
	(0.0016)	(0.0026)	(0.0048)	(0.0073)
T+2	0.0062***	0.0083***	0.0111**	0.0131*
	(0.0015)	(0.0028)	(0.0050)	(0.0067)
T+3	0.0043***	0.0051**	0.0084*	0.0091
	(0.0015)	(0.0026)	(0.0050)	(0.0075)
LnVCAge	-0.0079	0.0034	0.0002	0.0552
	(0.0398)	(0.0577)	(0.1437)	(0.2059)
LnFUNDAge	0.0815**	0.0926*	0.1956*	0.1983
	(0.0342)	(0.0515)	(0.1165)	(0.1997)
LnInvSize	0.1262***	0.1703***	0.2396***	0.1506***
	(0.0372)	(0.0428)	(0.0625)	(0.0569)
_cons	1.0130***	1.0287***	1.7864***	3.0298***
	(0.0740)	(0.1013)	(0.2112)	(0.3646)
Year	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
N	53,666	39,778	53,666	39,778
R-sq/ Wald Chi2	0.145	0.153	43.57	28.13
adj. R-sq/ Pseudo R2	0.144	0.151	0.245	0.317

Table 1.16: Subsample test (companies with patents only) (3-year window)

This table presents the results of IV & Heckman Two Stage estimations using 3-year window. The first column shows the first stage results, and the following two columns present the second stage results. The dependent variables are dummy variable of cross-border VCs, natural logarithm of the number of patents, the number of citations, the number of citations per patent, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses. LR chi2 is reported for the first stage probit estimation.

	First Stage	LnPATENT	lnCITATION	LnCIT/PATENT
3-year window	(1)	(2)	(3)	(4)
CBVC		0.276***	0.484***	0.157*
		(0.099)	(0.123)	(0.089)
NumVCs	0.574***	0.023	0.010	-0.109*
	(0.048)	(0.051)	(0.088)	(0.057)
LnVCAge	-0.024	0.065	0.169**	0.197***
	(0.021)	(0.061)	(0.078)	(0.064)
LnFUNDAge	-0.037*	0.011	-0.048	-0.057*
	(0.020)	(0.035)	(0.048)	(0.034)
LnINVSize	0.062***	0.185***	0.352***	0.257***
	(0.020)	(0.056)	(0.073)	(0.062)
LnGDP	-0.010	-0.206**	-0.386***	-0.275***
	(0.017)	(0.082)	(0.104)	(0.079)
MARKETDev	-0.383***	-0.050	0.409***	0.645***
	(0.043)	(0.076)	(0.098)	(0.127)
Ln_infow	0.021***			
	(0.007)			
_cons	-1.461***	2.613***	2.454***	-0.118
	(0.266)	(0.402)	(0.540)	(0.439)
lambda		0.527	2.003***	2.151***
		(0.454)	(0.583)	(0.502)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes
Wald chi2/LR chi2	1533.52***		1067.011***	
Chi2		0.148	0.114	0.195
adj. R-sq		0.121	0.089	0.166
N	1,562	1,562	1,562	1,562

Table 1.17: VCs from high innovation country

This table presents the results of IV & Heckman Two Stage estimations using 3-year window. The first column shows the first stage results, and the following two columns present the second stage results. The dependent variables are dummy variable of cross-border VCs, natural logarithm of the number of patents, the number of citations, the number of citations per patent, respectively. High Innovation VC is defined as top 25th percentile of the country GII (Global Innovation Index). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses. LR chi2 is reported for the first stage probit estimation.

	First Stage	LnPATENT	lnCITATION	LnCIT/PATENT
3-year window	(1)	(2)	(3)	(4)
CBVC		0.270***	0.424***	0.108
		(0.073)	(0.109)	(0.076)
NumVCs	0.530***	-0.065	0.061	0.062
	(0.040)	(0.059)	(0.082)	(0.054)
LnVCAge	-0.026	0.020	-0.034	-0.036
	(0.022)	(0.036)	(0.049)	(0.035)
LnFUNDAge	-0.037*	0.039	0.021	0.007
	(0.020)	(0.033)	(0.045)	(0.032)
LnINVSize	0.061***	0.108***	0.142***	0.060*
	(0.020)	(0.033)	(0.046)	(0.031)
LnGDP	-0.111***	-0.093***	-0.050	0.058*
	(0.019)	(0.035)	(0.046)	(0.034)
MARKETDev	-0.316***	0.050	0.238***	0.392***
	(0.043)	(0.085)	(0.084)	(0.078)
Ln_infow	0.000			
	(0.005)			
hgii_p25_VC	1.051***			
	(0.095)			
_cons	-1.349***	3.512***	4.270***	1.501***
	(0.276)	(0.543)	(0.749)	(0.488)
lambda		-0.523***	-0.321	0.148
		(0.192)	(0.264)	(0.187)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes
Wald chi2/LR chi2	1678.57***	162.29***	169.32***	259.65***
N	10,844	10,844	10,844	10,844

Table 1.18: High tech industry

This table presents the results of IV & Heckman Two Stage estimations using 3-year window. The first column shows the first stage results, and the following three columns present the second stage results. The dependent variables are dummy variable of cross-border VCs, natural logarithm of the number of patents, the number of citations, the number of citations per patent, respectively. High_tech is defined as industries in Biotechnology, communication, Computer related, Medical, and Semiconductor/Electric. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses. LR chi2 is reported for the first stage probit estimation.

	First Stage	LnPATENT	lnCITATION	LnCIT/PATENT
3-year window	(1)	(2)	(3)	(4)
CBVC		0.263***	0.397***	0.132*
		(0.080)	(0.107)	(0.076)
NumVCs	0.600***	0.187	0.399**	-0.064
	(0.046)	(0.130)	(0.174)	(0.123)
LnVCAge	0.000	0.014	-0.043	-0.031
	(0.020)	(0.036)	(0.050)	(0.035)
LnFUNDAge	-0.039**	0.012	-0.014	0.013
	(0.019)	(0.035)	(0.049)	(0.033)
LnINVSize	0.056***	0.155***	0.214***	0.034
	(0.018)	(0.038)	(0.056)	(0.037)
LnGDP	-0.000	-0.116***	-0.049	0.078**
	(0.016)	(0.033)	(0.046)	(0.033)
MARKETDev	-0.366***	-0.227	0.056	0.524***
	(0.041)	(0.140)	(0.115)	(0.125)
Ln_infow	0.018***			
	(0.007)			
High_tech	0.800***	-0.022	0.527	0.084
	(0.169)	(0.353)	(0.490)	(0.323)
_cons	-1.454***	2.105***	2.532**	2.121***
	(0.209)	(0.789)	(1.080)	(0.698)
lambda		0.451	0.871	-0.324
		(0.415)	(0.544)	(0.403)
Industry	No	No	No	No
Year	Yes	Yes	Yes	Yes
Stage	Yes	Yes	Yes	Yes
Wald chi2/LR chi2	628.28.35***	136.16***	155.09***	231.32***
N	10,844	10,844	10,844	10,844

Chapter 4: Social Connectedness and Cross-border VC Investments

Abstract

This study investigates the role of social connections in the cause and consequences in cross-border venture capital investments. Implementing a novel proxy of Social Connectedness Index, extracted from Facebook friend connections, I discover that cross-border VC investors are more likely to invest in portfolio companies located in socially connected countries. However, while such social ties reduce the likelihood of successful exits, they also enable portfolio companies to access diverse resources and knowledge spillovers, enhancing their innovation performance following cross-border VC investments. Furthermore, I employ instrument variable and Heckman two stage model to address the potential selection bias and concerns. The findings are robust to a variety of tests and econometric approaches for dealing with endogeneity problems. The findings underscore the role of geographical structure of social networks between countries in cross-border venture capital decisions contributing to the economic sociology and spatial economics literature.

4.1. Introduction

Venture capital (VC) investors specialize in identifying start-ups with high growing potential as well as high uncertainty and risks, arising from information asymmetry. Comparing to public companies, private companies disclose much less information, in the absence of SEC-mandated documentation, financial websites, and financial analyst profession recommendations. Consequently, VC investors make decisions based on the limited information from business plans provided by entrepreneurs, their interpersonal and organizational connections (Cumming and Dai, 2010; Nguyen et al., 2023). Asymmetric information makes it difficult for VC investors to differentiate between promising and inferior companies. Especially most of them are at the early stage and associated with much more pronounced information asymmetries (Gompers and Lerner, 1998; Cumming et al., 2016; Howell, 2020). Likewise, it prevents portfolio companies to convey their true values to investors (Humphery-Jenner et al., 2017). Furthermore, information asymmetry leads to other problems such as agency conflicts, adverse selection, and moral hazard, which are detrimental for investment performance.

However, VC investors are proficient in managing risk and addressing information and agency problems. Their investment decisions involve a sophisticated process that includes deal selection, due diligence, contracting, monitoring, strategy guidance, and staged financing, with the objective of enhancing portfolio company values (Gorman and Sahlman, 1989; Gompers et al., 2020; Weik, 2024). Nevertheless, the cost of oversight and monitoring is sensitive to the geographic distance, which impacts both monitoring expenses and communication effectiveness (Chen et al., 2010).

Greater distance leads to increased costs and reduced VC involvement, as demonstrated by Bernstein et al. (2016), who found a decline in VC participation as travel time rises. Similarly, Lerner et al. (1995) provided evidence of a preference for VCs to serve on the boards of geographically closer companies, a phenomenon referred to as local bias. Consequently, some VC firms specialize in specific regions, with some even applying the "20-minute rule," investing primarily in ventures within a 20-minute drive from their office (Cumming and Dai, 2010; Gompers et al., 2020).

However, with the growth of the VC industry, the geographic focus of investments has expanded beyond local areas, with VC firms increasingly investing across regions and even cross-border. VC industry experience increasing capital flows, number of deals, and broader geographic range in recent years (Nahata et al., 2014; Boryniec et al., 2023). The industry is no longer confined to proximity-based decisions but is gradually expanding its investment reach globally.

Problems of information asymmetry are more severe in cross-border transactions than equivalent domestic transactions (Portes and Rey, 2005; Humphery-Jenner et al., 2017). Beyond incurring additional costs, cross-border VC investors encounter challenges arising from cultural and legal differences, often referred to as the Liability of Foreignness (LOF) in the literature. Therefore, it is important to investigate how cross-border VC address the severe information asymmetry problem and mitigate the liability of foreignness.

Previous studies indicate that social connections influence cross-border VC decisions. Sorenson and Stuart (2001) emphasize that interfirm networks facilitate the diffusion of information across boundaries, thereby expanding the geographic scope of investments in the US VC industry. In addition, De Prijcker et al. (2012) and Schertler and Tykvova (2011) found that VC firms led by managers with significant foreign experience are more likely to invest heavily in international markets. However, the research about social network has been limited by the absence of comprehensive data reflecting social connections among individuals and geographic regions. The relation between social connectedness and cross-border venture capital investments has not been thoroughly explored.

Recently, an expanding body of research has started utilizing data from online social networking platforms such as Facebook, LinkedIn, and Twitter to analyse social connectedness. In this study, I employ the Social Connectedness Index (SCI), developed by Bailey et al. (2018a), which is constructed using Facebook friendship data to capture the relative intensity of connections between country pairs on this global social network. Therefore, I utilize this index to investigate the nature of this relationship. This study fills in the gap by examining the impact of social connections on cross-border VC investments selections and outcomes, especially innovation outcomes.

To test the hypotheses, I start with venture capital investments data from Eikon starting from 1996, and then I track the portfolio company outcomes until 2021. I test the role of social connectedness in cross-border VC investments selection, financial performance, and innovation performance. First, I conduct a counterfactual analysis on 2,587,898 potential VC-PC pairs to assess the likelihood of cross-border VC investment, utilizing logit and probit regression models. The findings indicate that cross-border VC firms are more likely to invest in portfolio companies located in countries with strong social ties. Furthermore, I examine the performance of cross-border venture capital investments, focusing on both financial and innovation outcomes. The results reveal a negative correlation between social connectedness and the likelihood of successful exits, showing that while social connections facilitate investment, they do not necessarily translate into higher success rates for exits. More importantly, I extend the analysis to the innovation performance of portfolio companies. I apply the Poisson pseudo-maximum likelihood estimator to evaluate the impact of social connectedness on the number of patents and citations. The results demonstrate that, despite the lower success rate in financial exits, portfolio companies backed by socially connected VC investors tend to produce significantly more patents and receive more citations, reflecting enhanced innovation performance.

Moreover, reasonable concerns exist regarding potential omitted or unobservable variables that may influence both social connectedness and company performance at the same time. Such omitted variables can result in biased estimates of the effect of social connectedness on firm performance. Therefore, I implement two methods to address potential concerns: using instrumental variables, internet user coverage in VC country, to control for endogeneity and employing the Heckman two-stage regression to correct the selection bias. The results are consistent with previous baseline estimates, indicating a significant negative relationship of social connectedness on success exits.

Taken together, the results support the hypotheses that cross-border VC investors are more likely to invest in portfolio companies within socially connected countries. Nevertheless, these close social relations adversely affect portfolio company performance, decreasing the likelihood of successful exits. Conversely, portfolio companies leverage diverse resources and knowledge spillovers by cross-border VCs, improving their innovation performance after cross-border VC investments.

This study contributes to three major areas of literature. First, it adds to the broader literature in economic sociology, especially the economic impact of social connectedness. Existing research shows social connectedness plays a significant role in people's financial decisions, like choosing which stocks to invest in (Cohen et al., 2008) or deciding to buy a house (Bailey et al., 2018b). In addition, it influences companies' key decisions such as hiring practices and productivity (Granovetter, 2018). Social connections also play an important role in international trading decisions (Kuchler et al., 2022). As a result, social connectedness determines investment outcomes (Ertug et al., 2022) and enhances the efficiency of stock markets and pricing (Hirshleifer et al., 2024). Furthermore, social connections facilitate information dissemination and investment opportunities, particularly in mergers and acquisitions (Cai and Sevilir, 2012) as well as in the crowdfunding market (Peng and Zhang, 2024). Research on VC industry has primarily centred on interfirm and networks rather than general regional connectedness. Sorenson and Stuart (2001) demonstrate that interfirm networks facilitate the dissemination of information and broaden investment opportunities. Gompers et al. (2016) focus on interpersonal connections and syndication, revealing that individuals tend to collaborate with those who share similar personal traits, though they incur higher costs for these high-affinity partnerships. The most closely related study to the current paper is Nguyen et al. (2023), which examine how social connections between regions and states in US influence VC investment selections and performance. However, I extend their study by investigating the intercountry social connectedness on cross-border VC investments. Furthermore, their analysis concludes at the point of the investment outcome in finance aspect. This study extends that exploration by focusing on the subsequent innovation outcomes.

Second, the study further contributes to the literature on spatial economics, by examining the role of geographic distance on economic activities. There is a fast-growing body of the literatures in corporate finance. Coval and Moskowitz (1999) document that causing by the information asymmetry, U.S. investment managers exhibit strong local bias to geographically proximate investments. While with networks and technology development recently, literatures record the reducing home bias trend in bank lending business and angel investments (Petersen and Rajan, 2002; Cowling and Brown, 2024). However, investigating geographic proximity in mergers and acquisitions, Uysal et al. (2008) find a negative relation of geographic proximity on deal performance. Furthermore, a substantial body of research explores the influence of geographic distance within the VC industry, particularly regarding deal selection and portfolio company value creation. Geographic distance significantly impacts VC investment choices and performance. For instance, Chen et al. (2010) observe that firms located in VC clusters outperform their rivals, and Cumming and Dai (2010) highlight that VCs exhibit strong local bias in their investments. Furthermore, VCs investing across borders face challenges not only from physical distance but also institutional and cultural differences, exacerbating information asymmetry and liability of foreignness, which results in increased costs, reduced benefits, and inferior performance compared to domestic investments (Zaheer and Mosakowski, 1997; Li et al., 2014; Nahata et al., 2014; Dai and Nahata, 2016). Other studies examine how VCs mitigate liability of foreignness and derive benefits from such investments (Tian, 2011; Espenlaub et al., 2015; Bernstein et al., 2016; Buchner et al., 2018; Khurshed et al., 2020). However, few studies investigate how VCs select cross-border investment opportunities. This research aims to fill this gap by examining the deal formations, while also extending the analysis to evaluate investment outcomes in both finance and innovation.

Third, the findings shed light on the factors driving corporate innovation. The existing literature identifies several determinants, such as female representation on boards (Chen et al., 2018), board diversity (An et al., 2021), overconfident CEO (Hirshleifer et al., 2012), risk-taking behaviour of CEOs (Bernile et al., 2017), an exploratory mindset among CEOs (He and Hirshleifer, 2022), high-quality top management (Chemmanur et al., 2019), and tolerance of early failures while rewarding long-term success (Manso, 2011) as crucial for corporate innovation success. Notably, this study adds to the expanding literature on the role of VC investors in fostering innovation. Lerner et al. (2011) emphasize the long-term positive impact of private equity on innovation. Specifically, Tian (2012) points out that VC syndication enhances innovation, while Tian and Wang (2014) suggest that VC investors' tolerance of failure drives innovation. Chemmanur et al. (2014) argue that corporate venture capitals are more effective at boosting innovation compared to independent venture capitals. Recently, Ewens and Marx (2018) report that the replacement of founders can lead to increased innovation. However, most of VC study on innovations are in domestic level, due to the data limitation. I use the international patent database Orbis-IP and extend the literature by studying the role of cross-border VC investors on innovation, combining with social connectedness between countries. This study is built on Bailey et al. (2018a), which using Social connectedness Index (SCI) and patent citations to reveal that social connection facilitates the diffusion of knowledge. In the realm of SCI, I further explore the social connectedness in cross-border VC investments. This is the first study to examine the innovation outcomes of inter-country social connectedness between VC firms and portfolio companies. by providing a more detailed quantification of the connections between countries and examining the innovation outcomes of portfolio companies.

The remainder of this chapter is structured as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 introduces the database and sample selection process. Section 4 illustrates the constructions of the variables, while Section 5 provides summary statistics. Section 6 details the empirical tests and methodology, followed by conclusions in Section 7. Finally, Section 8 is appendix, including tables mentioned in the chapter, and variables definitions.

4.2. Literature Review and Hypothesis Development

In this section, I review literature on social connections, and develop three hypotheses for further testing.

4.2.1 Social Connections

Individuals tend to build connections based on homophily (Lazarsfeld and Merton, 1954), favouring those with similar ascribed traits, like race, gender, age, and common achieved characteristics, such as religion, values, attitudes, preferences, education, and other types of life experiences (Ertug et al., 2020). Homophily ties similar individuals, leading to higher interactions (Reagans, 2005). For example, and similarity between salespeople and customers boosts sales effectiveness in U.S. life insurance sector (Crosby et al., 1990); researchers with shared ethnic backgrounds collaborate more often (Freeman and Huang, 2015); funders are more likely to support founders of the same gender in fundraising (Greenberg and Mollick, 2017, Ewen and Townsend, 2020). Furthermore, bonds between individuals strengthen the connections between regions. Bailey et al. (2020) provide evidence that connections are stronger between European regions with residents share similarity in age, education, common languages, and religions. In addition, connections between regions are related with geographic proximity, historical ties, political boundaries (Bailey et al., 2018a).

Furthermore, social connections shape beliefs, behaviours, and economic decisions. Dimmock et al. (2018) found that coworkers influence misconduct among individuals more who with shared ethnic backgrounds. In addition, social connections are associated with product purchases and consumer decisions. Gilly et al. (1998) showed that word-of-mouth impacts consumer behaviour. Similarly, Nitzan and Libai (2011) observed that mobile users are more likely to switch providers if socially connected to others who do so. Likewise, Bailey et al. (2018b) identify social connections as a factor in housing choices, such as renting or buying. More importantly, social connections also contribute to financial decision-making, including stock recommendations (Pursiainen, 2022) and stock pricing (Hirshleifer et al., 2024).

The impact of social connections extends beyond individual decision-making to influence corporate decisions as well. Employers are more likely to recruit through social networks (Granovetter, 2018), and countries practise more international trades with socially connected countries more than others (Kuchler et al., 2022). In addition, social ties influence financing and fund raising. Investors are 50% more likely to invest a crowdfunding project when endorsed by investor peers and 11.2% more when the projects from the regions where investors are strongly social ties to (Peng and Zhang, 2024). Likewise, angel investors are inclined to select project through social connections (Sudek, 2006, Cumming and Zhang, 2019). Noteworthily, social connections also impact VC investors decisions. Gompers et al. (2020) highlight that VC investors' connections, such as professional networks, or referred by other investors, or from a portfolio companies, make up more than half of the VC investments in their study sample. In addition, social network expands the spatial radius of exchange and connect startups and VC investors across border (Sorenson and Stuart, 2001). What's more, accessing to local networks enable cross-border acquirors to mitigate the liability of foreignness (Li et al.,2014, Humphery-Jenner et al., 2017). Therefore, it is vital to investigate the role of social connections in cross-border VC investments.

4.2.2 Hypothesis Development

This study draws inspirations from Bottazzi et al. (2016), which analyses the effect of trust in VC investment decisions. Using a hand-collected dataset of European VC deals and the trust measure from Eurobarometer survey, they reveal the relation between trust among countries and VC investment decisions. Bottazzi et al. (2016) demonstrate that trust influences VC firms to increase their investments in portfolio companies. The likelihood of an investment is positively correlated with the level of trust between the party countries. However, greater trust also raises the willingness to take on higher-risk investments, ultimately lowering the success rate. Additionally, they uncover links between trust and deal structures, including the investment stage, syndication decisions, and the design of contingent contracts. Building on their research, I use novel data from the Social Connectedness Index (SCI) based on Facebook user connections to measure social connectedness between countries. The social connectedness index data allow us to extend the research and examine directly empirical relationship between social connectedness and VC investments decisions and outcomes. Given the liabilities of foreignness and distances in geographic, cultural, and institutional faced by VC investors, I examine the role of social connections in deal formation, successful exit. More importantly, I expand the scope of the study by exploring how social connectedness affect innovation outcomes in cross-border VC investments.

H1: Deal Formation

I infer that social connections facilitate the formation of cross-border VC investment deals and reduce information asymmetry from three aspects. First, the networks disseminate information and raise awareness to connected countries and investment opportunities. In addition, the connections reduce information frictions, improve communication efficiency, and alleviate economics barriers. Moreover, social connections help to build trusts, and foster investments.

Transmit Information

I argue that social connections transmit information, and further influence deal formations. As it is indicated in previous literatures, connected individuals convey information through social networks (Granovetter, 2018). Cohen et al. (2008) discover that shared educational networks between mutual fund managers and corporate board members influence their stock selections and performance. Specifically, they show that portfolio managers make larger, concentrated investments in stocks tied to the networks and, in turn, achieve significantly better returns on these holdings than on both their nonconnected holdings and connected firms they choose not to invest in. This premium in returns is attributed to the information circulating within the network. Besides, social connections between firms' boards transmit information, and leads to greater synergy sources, and a better performance in M&A transaction (Cai and Sevilir, 2012). In addition, extending beyond domestic transactions, Rauch and Trindade (2002) capture social networks disseminate information about buyer-seller in international trades.

Moreover, geographical structure of social networks assists information spread. Kuchler et al. (2022) propose that social ties between regions transmit investment information. This the dissemination of information through social connections between regions has been recorded in various financial markets. Hirshleifer et al. (2024) examine the role of social connectedness of counties in US in stock market. They find the positive relations between social connectedness and information spread. It is shown that firms in the highly socially connected areas experience stronger immediate responses in price, volatility, and trading volume, which ultimately facilitates the timely incorporation of news into prices. Therefore, they argue that information spread more rapidly, and investors react more actively to firms located in more socially connected counties. Furthermore, Peng and Zhang (2024) illustrate social connections transmitting information in crowdfunding market. Information, such as details on potential project, and the economic conditions of the project's location, flows through social networks. They explain that such information supports backers make more informed decisions and reduces the uncertainty they encounter. Therefore, they observe that investors are 11.2% more likely to fund projects from socially connected regions than others. In addition, social ties between regains are also impact investment decisions of institutional investors. Kuchler et al. (2022) denote that institutional investors are also inclined to firms located in regions with stronger social ties. Additional information from social ties increases institutional investors' awareness of the project and informs their decisions.

Furthermore, social connectedness has long been emphasized by VC investors as a key factor in their investment. Although the VC industry involves high growth potential, significant uncertainty, and substantial information asymmetry, VC firms interact with capital markets, customers, management teams, and additional investors for start-ups and add values to portfolio companies (Gompers et al., 2020). However, cross-border VC investors face more challenges from geography, culture, and institution distances, leading to more pronounced information asymmetry and LOF compared to domestic investors. Therefore, cross-border VC investments experience increased costs and reduced benefits. What's more, the foreignness also affects people's preference on social connections. As indicated by Granovetter (2018) and Sorenson and Stuart (2008), in such high-risk setting like VC industry, actors present strong preferences to interact with proximate individuals. Therefore, social connections play a vital role in the cross-border VC investments.

I argue that social connections support information spread especially abroad, leading to cross-border deal formation. Lindsey (2008) denotes the information and resources sharing through social network between portfolio companies with a shared common venture capitalist. In line with this, social connections not only transmit information for common VC firms, but also outside information such as distant opportunities, so that VC firms expand the VC investment radius. Sorenson and Stuart (2001) illustrate that social networks decrease the space-based constraints on economic exchange and diffuse information across boundaries. Consistent with this, Rauch (2001) find that social networks between countries facilitate information transferring abroad. Therefore, I infer that the impact of social connections extends beyond domestic market to international transactions.

Nguyen et al. (2023) notice that social connections expand VC investors' recognition of portfolio companies that are geographically distant but socially proximate, and VC firms invest more capital in portfolio companies in socially connected regions than other companies. However, the role of social connections between countries in influencing VC investment decisions remains largely unexplored. In the same vein, I speculate that social connections between countries promote information flow and increase VC investors' awareness of portfolio companies from other countries, which might be overlooked because of geographic distance.

Alleviating Information Frictions

Furthermore, I argue that social connections alleviate information frictions and affect deal formations. As documented in previous literatures, information frictions impede international trade (Steinwender, 2018). Firms from different cultural and institutional background experience increased trade barriers, and excessive trading and monitoring cost for investment abroad.

Similarly, compared to domestic VCs, cross-border VC investors face more information asymmetry problems and information frictions, which are some challenges that impede the complete and accurate exchange of information among market participants. For example, increasing geographic distance is associated with increasing costs of obtaining information, and conducting transactions (Nahata et al., 2014), which consequently exacerbate the challenges and expenses of screening, monitoring, advising, and supporting remote portfolio companies (Buchner et al., 2018). Specially, greater distances induce some extra costs of contracting and monitoring (Sapienza et al., 1996; Chen et al., 2010). Moreover, geographical distance between the domicile countries of VC investors and portfolio companies, reduces the effectiveness of information transmission and affects the ability of VCs to evaluate high quality investment prospects (Cumming and Dai, 2010). Besides that, Colombo et al. (2019) suggest that long distance can dilute investors' ownership stakes, resulting in a loss of control over portfolio companies and consequently reducing the associated benefits. In addition, cultural and institutional distances affect cross-border VC investments performance (Li et al., 2014).

However, a transparent information environment reduces information frictions and attracts foreign VC firms (Guler and Guillen, 2010). In addition, researchers suggest that social connections reduce information friction in transactions and facilitate trades. Rauch (2001) examine the role of social network in international trade and find that transnational networks support contract enforcement, and thus alleviate information friction in international trade. In addition, Rauch and Trindade (2002) provide evidence that social connections discourage opportunistic behaviour in international trades.

Moreover, social connections enhance coordination and communication among connected parties. Ertug et al. (2022) observe that similar socially connected parties are more likely to collaborate efficiently and communicate effectively. Furthermore, a better communication facilitate trade by alleviating informal trade barriers, including contract enforcement frictions and search costs due to information frictions (Chaney, 2016). Consistent with this, Bailey et al. (2018a) highlight that social connections are associated with decreased trade costs. Therefore, scholars suggest that social connections alleviate information frictions. Then I infer that cross-border VC investors can also benefit from social connections and shape their investment decisions.

With the challenges from information frictions, cross-border VC investors are more selective in choosing investment opportunities and have developed methods and strategies to mitigate the liability of foreignness and information frictions, such as different risk assessment in screening and target selection (Wright et al., 2005), more rigorous due diligence than domestic ventures (Nahata et al., 2014), and staging financing (Tian, 2011). More importantly, VC investors utilize social connections to improve investments. Nahata et al. (2014) and Buncher et al., (2018) demonstrate that syndication with other investors, especially local VCs, mitigate information frictions for cross-border VC firms. Dai and Nahata (2016) further explain that local VCs play an important role in reducing information collection, communications, and monitoring. The participation of local VCs mitigates the LOF and alleviates information frictions.

Building on this, I speculate that social proximity between regions and countries reduces information asymmetry, enabling cross-border VC firms to collaborate more effectively with ventures. Consequently, cross-border VCs are more likely to invest in socially connected countries, where informal trade barriers and information frictions are minimized.

Trust

I argue that social connections build trusts, and further impact deal formations. Strong social connections further develop to trust and mutual understanding (Granovetter, 2018). Sociologists observe that homophily is a key factor in shaping social relationships, as individuals tend to build connections with those who share similar values and beliefs (Sorenson and Stuart, 2001). Furthermore, similarities lead to attraction, smoother coordination, better communication, and enhanced trust (Ertug et al., 2020). Social connection becomes a channel to form trust (Li et al., 2014). As a result, individuals with a higher level of trust are more likely to engage in an economic transaction (Granovetter, 2018). Mizruchi and Stearns (2011) indicate that bank officers tend to seek consult their strong ties and trusted colleagues for information and deal approvals. On the other hand, lack of trust reduces investors participation in stock market. Guiso et al. (2008) explain that concerned about the risk of fraud, investors are less likely to buy stocks or commit significant capital. Moreover, lack of trust intensifies the impact of high participation costs. Consistent with this, they also find that a lower bilateral trust leads to less trade between two countries.

In addition, trust between regions shapes economic decisions, as people are more inclined to trade and invest with partners from trusted regions. Kadri Ekinci and Alp Erturk (2007) find that regions with a higher level of trust are more likely to integrate their financial markets, reflected in reduced barriers to trading financial assets like stocks and bonds. In addition, Kuchler et al. (2022) state a positive relationship between the likelihood of institutional investors investing with the region social ties. Firms located in regions with higher social proximity are more likely to be selected by institutional investors and have higher valuation and liquidity.

Consistent with this, geographic structure of trust also impacts VC firms' decisions. Bottazzi et al. (2016) suggest a positive correlation between bilateral trust between countries and VC firms' investments. VC firms are more likely to invest in companies located in them trusted countries, so that they share information more frequent and openly. Moreover, as I mentioned, social connections transmit information. In addition, soft information including social belief like trust, also transfers through social connections. Bottazzi, et al. (2016) highlight that when VC firms fund new ventures with limited hard information such as concrete data, and involve significant uncertainty, and the ventures can potentially for opportunistic behaviour. Instead, investors are more likely to depend on soft information. Higher trust increases the propensity of receiving investments. Therefore, I conjecture that social connections serve as the channel of trust and elevate the likelihood of attracting cross-border VC investments.

Overall, with all factors considered, I argue that cross-border VCs are more likely to invest in socially connected countries, as VC firms can leverage regional social networks to identify promising investment targets, overcoming information constraints, and foster trust with each other. I hypothesis that:

H1: Cross-border VCs are more likely to invest in socially connected countries.

H2: Success

In this session I would like to examine the role of social connections on investments success exit. Following Gompers et al. (2005) and Bottazzi et al. (2008), I define successful exit as the invested company experience either an IPO or an acquisition after VC investments. It is widely acknowledged that VC firms play an important role in portfolio companies growing and success. In addition to provide funding and financing to startups, VC firms provide services, such as recruiting skilled management, better incentives to empolyees and management, and leveraging networks of suppliers and potential customers. As a result, VC firms add values to portfolio companies, and considerably enhance the probability of success of these companies (Gompers et al., 2020). Chemmanur et al. (2011) state that VC-backed companies outperform non-VC-backed companies with higher productivity, and a greater likelihood of successful exits. The improved performance results from effective screening and monitoring by VC firms, which increases sales volume and reduces increased production costs, particularly for those backed by reputable VCs.

Furthermore, researchers have extensively examined how VC firms enhance portfolio companies' performance and improve the likelihood of successful exits. For example, Nahata (2008) highlights that VC reputation is positively associated with successful exits, and later-stage investments are more likely to succussed. Tian (2012) finds that syndication enhances firm value in both product and financial markets. Ewens and Marx (2018) and Conti and Graham (2020) emphasize leadership changes, such as replacing founder or CEO, is beneficial for company performance. Moreover, external market condition is important for VC firms to decide the exit timing. Gompers et al. (2020) reveal that VC firms prefer to exit during robust IPO and M&A markets. Additionally, Bernstein et al. (2016) underscore the importance of onsite VC monitoring in driving company performance. In other words, VC firms are difficult provide sufficient monitoring and assistance to distant companies and shrink the likelihood of successful exits. Therefore, Tian (2011) illustrate that VC investors implement stage financing to monitor distant companies. VC firms tend to invest in companies located farther away through more financing rounds, with shorter intervals between rounds, and smaller investments per round. As a result, staging boosts company performance, and increases their propensity to go public.

In addition, VC firms investing abroad involves more challenges other than distance monitoring. Liabilities of foreignness arise from geographical, cultural, and institutional disparities and increase investors costs and diminish benefits. Li et al. (2014) demonstrate that institutional and cultural differences hinder the efficiency of VC activities, and negatively impact investment performance, particularly exit success. While cross-border VC investments yield lower returns than equivalate domestic ones, investors are compelled to invest abroad to diversify portfolios and seek new growing opportunities outside of the saturation domestic markets. Moreover, VC investors have acquired knowledge and expertise to manage risks and address liabilities of foreignness. For example, investing in later rounds and in larger, more mature companies which provide more transparent information to cross-border VC investors (Dai et al., 2012); syndicating with local VC to spread risks and to mitigate the liability of foreignness (Makela and Maula, 2008). In addition, Cumming et al. (2016) exhibit evidence that portfolio companies with international investor base are more likely to have successful exits and higher valuation in M&A deals and IPO proceeds. Furthermore, Devigne et al. (2016) denote that foreign VCs are less embedded with local community, which alleviates individual decision bias so that VCs make rational decisions and less likely to escalate from commitment. What's more, I speculate that social connections play an important role in cross-border VC investments success exits.

Previous studies indicate that social connections can undermine productivity and performance, because of homogeneity, which induces ingrown groupthink, and familiarity bias. Specifically, Ertug et al. (2022) imply that social connections convey overlapping information and reduce the diversity of information. Consequently, homogeneity undermines the productivity, while heterogeneity in social connections increases productivity in work group. Lee et al. (2014) suggest that alignment in political ideologies between the CEO and independent directors decreases firm value and operating profitability. In addition, I infer that closer social connection leads to greater risk appetite and decision bias. Papaioannou (2009) illustrate that investors are willing to take more risks when dealing with people through social ties. In addition, Granovetter (2018) observe that investors accept a lower expected hurdle rate and loosen stringent due diligence standards on a project when they work with familiar others in their social connections. Furthermore, Gompers et al. (2016) examine the cost of friendship in VC decision making and find that investors pay extra costs for their friendship. Social connections and high affinity foster social conformity and groupthink, leading to inefficient decision-making, shown as decreased the probability of domestic VC investments success. The inefficient decision making, also known as familiarity bias, stems from social proximity, and eventually causes VC investors' ineffective monitoring and worse investment performance (Nguyen et al., 2023). In alignment with this, Bottazzi et al. (2016) demonstrate a negative correlation between trust and VC deals success exits.

Therefore, I infer that social connectedness reduces the diversity of information, strengthens decision bias, and further undermines the success exits of cross-border VC investments. Thus, I hypothesis that:

H2: There is a negative association between social connectedness and cross-border VC investment successful exits.

H3: Innovation

In addition to analysing cross-border VC investments successful exits, I next evaluate the portfolio company innovation performance. Innovation is crucial for firms to maintain long-term competitive advantage and drive economic growth (Aghion and Howitt, 1992; Gompers et al., 2002).

Scholars argue that management team and corporate culture influence corporate innovation significantly. Chen et al. (2018) suggest that the female on boards increase innovation; An et al. (2021) illustrate that diverse board, professional diversity in particular, performs superior advising capacity and benefits innovation. Furthermore, Chemmanur et al. (2019) suggest firms led by high-quality top management team allocate more resources in research and development (R&D) and produce a greater number of patents, including those of superior quality. In addition, risk taking and overconfident CEO encourage more innovation (Hirshleifer et al., 2012, Bernile et al., 2017, He and Hirshleifer (2022). In addition, Baranchuk et al. (2017) find that managers are driven to enhance innovation through "innovation-friendly" incentive schemes, including deferred compensation, extended vesting periods for stock options, and some protection from takeover threats. Consistent with this, Manso (2011) and Tian and Wang (2014) highlight tolerance for failure supports innovation.

Tian and Wang (2014) conclude the pressures for innovation are mainly from two sources, capital constraints and career concerns. Policies on relaxing these two frictions are beneficial for innovation increasing. Align with this, Hsu et al. (2024) show that director job insecurity negatively impacts innovation. They argue that job insecurity fosters director myopia, causing firms to adopt a conservative approach and reduce investments in risky, long-term innovation projects. In addition, financing plays a critical role in driving innovation. Nanda and Rhodes-Kropf (2017) find that active financial markets foster innovation, as investors are more likely to fund experimentation with low financing risk and in a hot financial market. Furthermore, investment in innovation is a long-term activity, and innovation often declines when firms focus on short term goals (Almeida et al.,2024). For example, He and Tian (2013) discover that firms with greater analyst coverage exhibit reduced innovation, with analysts pressuring managers to prioritize short-term objectives over innovation. Consistent with this, Lerner et al. (2011) state that such short-term pressures could negatively impact firms' long run performance. Therefore, with funds support from VC investors, portfolio companies are relieved from the financing risks. Prior research indicates that companies backed by VC firms are generally more innovative compared to those without such support (Hellmann and Puri, 2000). Also, Kortum and Lerner (2000) demonstrate that more venture capital activities is associated with a substantial increase in patenting.

Moreover, some specific VC activities increase innovation. Tian (2012) and Chemmanur et al. (2014) find that, specifically, VC syndications and corporate venture capitals (CVC) allow portfolio companies to access to more resources, thereby improving their innovation capacity. Furthermore, Bernstein et al. (2016) show that on-site involvement and active monitoring by VC firms generally enhance innovation. Additionally, Conti and Graham (2020) highlight that prominent VCs influence CEO turnover decision, and it leads to increased innovation in startups. What's more, previous research highlights foreign investors nurture innovation. Guadalupe et al. (2012) identify a positive association between multinational foreign ownership and innovation through enhanced productivity and adopting foreign technologies. Similarly, Hsu et al. (2021) find that in cross-border M&A deals, firms from low-innovation countries increase patent output and R&D investment after acquiring targets in high-innovation countries. In research about cross-border VCs, Chahine et al. (2022) show that foreign venture capital can access to foreign research, which leads to innovation increase.

Build on this, I extend the research by examining the role of social connections of cross-border VC on innovation. Based on previous literature, I hypothesize that social connections enhance innovation through knowledge spillover, efficient communication, and trust**.**

First, social connections facilitate information exchange and promote knowledge spillover. Similar to local bias in investor preference, geographic distance matters to knowledge spillover. The existing literatures indicate that knowledge spillovers are highly localized (Jaffe et al., 1993; Thompson and Melanie, 2005). Seru (2014) highlight that firm boundary is critical to resources allocation. However, information could be spread through social networks, and drive localized knowledge to diffuse to other parties (Sorenson and Stuart, 2001). Although long geographic distance exacerbates information asymmetry and hinder innovation, increased transparency can mitigate these costs, ultimately enhancing innovation (Brown and Martinsson, 2019). Agrawal et al. (2008) also illustrate that social networks enhance information transfer and accessibility for portfolio companies. Therefore, social proximity is advantageous to overcome the challenges raised by physical distance, which is also referred as network-based theories of innovation diffusion (Sorenson and Stuart, 2001). Moreover, Granovetter (2018) highlight that novel information flowing through diverse social connections is valuable for innovation outcomes. Beyond transferring the existing knowledge, geographical structure of social networks increases the exposure of the region to receiving and adopting new ideas (Glaeser, 1999). Furthermore, Choudhury (2022) implies that social connections also facilitate to recombine knowledge and improve innovation. Therefore, I conjecture that social connectedness transfer more and diverse information to portfolio companies and enhance their innovation outcomes.

Second, social connections enable communication more efficiently. Building on homophily, connected individuals share common values and norms, which in turn leads to smoother coordination and better communication (Ertug et al., 2022). In addition, Rogers and Bhowmik (1970) assert that communication is more effective when parties share similarities. Similarly, McPherson et al. (2001) state that social connections create contexts and eases communication and, which results in enhanced mutual understanding and smooth communications. Furthermore, Cohen et al. (2008) present the power of efficient communication. They show that mutual fund managers who share education background coordinate with their connections better and outperform than peers. The superior performance, believed by Gompers et al. (2016), result from smooth communication and tacit information delivery. Therefore, I speculate that social connections enable parties to communicate effectively, mitigate communication challenges, and overcome cultural differences in cross-border VC investments, which leads to productive joint decisions and better innovation outcomes.

Third, repeated interactions in social connections breed trust, which accelerate innovation. Trust grows from social connections, as Ertug et al. (2022) demonstrate that homophily not only fosters social ties, but also enhances trust between parties. Likewise, Hain et al. (2016) find that generalized institutional trust between regions is built through frequent and open information sharing, and trust affects the rate of social exchange absorption. Previous literature study the role of social trust in innovation. Kong et al. (2021) observe that increased CEO trust level increase corporate innovation significantly. Moreover, Xie et al. (2022) discover that trust fosters innovation by stimulating collaboration and cultivating resilience to failure. Specifically, they demonstrate that trust supports technological transfer and collaborative innovation activities; and trust reduces concerns about the high costs of innovation failure for firms and employees. Therefore, I infer that social connection is a channel for trust growth, and further promote innovation.

In conclusion, I hypothesis that social connections enhance innovation by knowledge spillover, reduced communication challenges, and trust growth.

H3: There is a positive association between social connectedness and portfolio company innovation performance.

4.3. Data and Sample Selection

In this part, I demonstrate the databases used in this study and the procedure of selecting the sample.

4.3.1 Database

The data comes from various sources. The main investment data are obtained from Refinitiv Eikon database provided by Thomson Financials, where I extract all VC firms, portfolio companies, and investment related information. I start with all VCs investments worldwide from 1996 and 2021. As Khurshed et al. (2020) imply that the globalization of VC industry started in mid-1990s, I start the sample from 1996, and focus on the portfolio companies received their first round of financing in or after 1996. In the sample for the second hypothesis test, I stop in 2017 to enable to evaluate companies' performance, I track them through beginning of 2021.

The social connectedness data is derived from de-identified administrative data on active users from Facebook, provided by Bailey et al. (2018a). They construct Social Connectedness Index (SCI) to proxy the social connectedness between two nations of VC firm's headquarters and the portfolio company's headquarters. Social connectedness data is ultimately from Facebook, which is a global online social media platform, connecting 2.7 billion monthly active users worldwide as of the second quarter of 2020, including 410 million users based in Europe, 256 million in the U.S. and Canada, 1.14 billion in the Asia-Pacific region, and 892 million in the rest of the world, except for countries where platforms like Facebook are banned, such as China, Iran, and North Korea. Facebook maintains a substantial presence in many countries globally.

The Social Connectedness Index is composed on friendship links on Facebook and users' country locations. The Social Connectedness Index between pairs of countries corresponds to the relative probability of a friendship link between Facebook users in the two countries. In addition, to assess the intensity of social connectedness among countries with different population sizes and various rates of Facebook usage, the index is adjusted based on the number of users in each country. Specifically, the Social Connectedness Index, $SCI_{i,j}$, is calculated by the total number of friendship connections between individual users in country i and individual users in country j, divided by the product of the number of Facebook users in those countries, i and j, as shown in the equation:

Equation 3: SCI index

$$SCI_{i,j} = \frac{FB_{connection}s_{i,j}}{FB_{user}s_i * FB_{user}s_j}$$

The user numbers for both countries are rescaled to range from a minimum of 1, and a maximum of 1,000,000. Thus, the Social Connectedness Index measures the relative likelihood of a Facebook friendship link between a given Facebook user in country i and a given user in country j. In total, the index involves pairwise social connectedness among 170 countries, resulting in $170 \times 169 = 28{,}730$ unique country-pair combinations.

Moreover, to measure innovation output, I use patent data from the Orbis Intellectual Property (Orbis-IP) database by Bureau van Dijk. Orbis-IP has become a valuable resource in recent innovation studies (Deng et al., 2022; Nathan and Rosso, 2022; Xie et al., 2022). It includes comprehensive global patent information from major patent offices, such as the UK Patent Offices, European Patent Offices, US Patent Offices, and Patent Corporate Treaty, dating back to 1900. The dataset provides company-level details, including geographic location, financial data, ownership structure, and patent portfolios, along with patent-level information such as ownership, citations, and transaction data. This allows us to assess both the quantity and quality of innovation, facilitating exploration of the effects of social connectedness on innovation outcomes.

In addition, following Cumming et al. (2016), I gathered country macroeconomic data from World Development Indicators Database (WDI) in World Bank; and I collected country geographic and language data from CEPII-Gravity database (Nahata et al., 2014). Moreover, country legal origins data are obtained from Porta et al. (1998).

4.3.2 Sample Selection

The sample selection process starts with all VC investments from Eikon since 1996. I only include companies who get investments all from VC investors, and I further select firms who received investments since the first round and track the effects of the initial investment. As Li et al. (2014) suggested, the initial funding round is critical for VC investor, implying VCs selection, assessment, and other important strategic decisions of portfolio companies. In addition, this can mitigate alternative causes for VC firms exit and portfolio company innovation performance outcomes and address potential reverse causality. Furthermore, I exclude the firms in stage of "other" and "real estate" and no geographic information shown. Then I select cross-border VC deals, which is defined as the headquarter nations of VC firms and portfolio companies are different. Given the VC firm information, and portfolio company (PC) information, I created two samples in the analysis.

In the first part of the tests, I investigate cross-border VCs entry decisions, specifically the role of social connectedness on VCs to make the cross-border deal decision. Previous studies of social connection formation analyze every possible dyad and use logistic regression estimate the effects of a covariate vector on the likelihood of the social connections (Sorenson and Stuart, 2001; Bottazzi et al., 2016; Quas et al., 2021; Ewen et al., 2022). Moreover, following Nguyen et al. (2023), I use the 2019 sample to test deal formation because it is the year most closely aligned with the available social connectedness measure. Therefore, consistent with their approach, I perform a counterfactual analysis by constructing the first sample through randomly pairing each VC firm that made an investment in 2019 with a PC that it didn't fund, so that I construct the sample of all potential VC-PC dyads, which consists of 3,265,037 pairs between the 1,289 VC investors, and their 2,533 portfolio companies (PCs), and includes all realized as well as unrealized pairs for VCs and PCs are involved in investments in year of 2019. After excluding observations with unavailable SCI data, the final sample comprises 2,578,898 observations.

In the second part of the tests, I examine the relationship between social connectedness and investment performance, specifically exit success, together with portfolio company innovation ability. I include all realized deals since 1996. Furthermore, Hochberg et al. (2007) indicate that on average, it takes VC investors 5 years to develop the outcome of the investments. So, the sample includes investments made up to 2017, with the outcomes can be observed until 2021. To alleviate concerns associated with the liability of foreignness, the analysis of social connectedness and deal financial and innovation outcomes is conducted using only realized cross-border VC deals. Furthermore, I remove duplicate VC-PC pairs when the VC invests in multiple rounds to the portfolio company in the sample, to prevent redundancy in the exit outcomes. Therefore, I end up with 24,399 unique VC-PC pairs in the sample, involving 3,318 VC firms and 16,848 portfolio companies. Excluding observations with missing SCI values, the final sample consists of 19,377 observations.

4.4. Variable Definition and Construction

In this session, I present the main variables I used in the tests, and their constructions.

4.4.1 Dependent Variables

In the first part of the tests, I assess how social connectedness effect the probability of cross-border VC firms investing in deals overseas. I implement the dependent variable outlined by previous study about probability of deal formations (Sorenson and Stuart, 2001; Bottazzi et al., 2016; Ma, 2020), using a binary dummy variable, DealHappen, that that equals one for realized pairs which indicates that if the VC firm invests in a specific portfolio company and of zero otherwise.

Furthermore, in the second part of the tests, I investigate the relationship between social connectedness and investment outcomes of the realized deals, including VC investor exits performance and portfolio company innovation outcomes. I track the performance for investments made up to 2017 to determine their success exits, allowing for a minimum five-year window for achieving an exit (Hochberg et al., 2007). Moreover, consistent with prior research on VC exit outcomes (Nguyen et al., 2023; Liu et al., 2021; Cumming et al., 2016; Dai and Nahata, 2016; Devigne et al., 2013), I evaluate exit performance at the deal level by assessing whether the venture is acquired through M&A or goes public through initial public offering (IPO). VC firms achieve higher returns through IPOs, which also motivate entrepreneurs to work harder as they prefer retaining control in public firms over acquisitions. However, when IPOs are unfeasible due to unfavourable market conditions or the inability of a company to sustain as a standalone entity, selling to larger acquirers becomes an alternative exit strategy for both VCs and entrepreneurs (Lerner,1994; Cumming et al., 2005; Nahata et al., 2014). Therefore, I define successful exit as VC firm exit either through IPO or M&A. I code *Success* equals to 1 denoting a successful exit, while 0 indicates otherwise. Since data on investment returns at the firm level are often unavailable (Devigne et al., 2016; Hochberg et al., 2007), the measurement provides a suitable approximation of VC fund returns, and it is widely adopted for assessing VC performance, as capital gains for VC firms predominantly arise from IPOs or acquisitions (Gompers et al., 2005; Nahata et al., 2014).

Besides VC exits, I also examine how social connectedness effect portfolio company innovation performance. I deploy the number of patents, and number of citations to measure the portfolio company both innovation quantity and innovation quality. Following Bena et al. (2017), I measure innovation quantity by counting the number of patents applications granted to a portfolio company after 3 years of receiving VC funding. Specifically, I employ application year to mark the innovation date, as it closely reflects the timing of the invention, and more accurately represents the outcome of innovation than the grant year (Bernstein et al., 2016; Ma, 2020). In addition, I adopt the approach of Lerner et al. (2011) to assess innovation quality by tracking patent citations in during the grant year and the following three years. Moreover, citation count is measured by the number of forward citations, representing the number of times a patent is cited by subsequent patents. Higher citation counts indicate a greater impact of the patent.

4.4.2 Independent Variables

I adopt Social Connectedness Index (SCI) from Bailey et al. (2018a) as the main independent variable to measure the social connectedness between countries. SCI is based on the anonymized administrative user information on Facebook, such as their locations on their profile, device, and connection information, to measure the intensity of social connectedness between countries.

Previous studies indicate that Facebook friendships is a valid metric to proxy the real-world friendship networks and social connectedness, where connections are established with mutual consent from both individuals. In contrast, other online social media platforms, such as Twitter, allow for one-sided connections, like following celebrities, where mutual consent is not required to create a connection. In addition, Duggan et al. (2015) confirm that Facebook friendship patterns, between states and regions, are closely related to real-world friendship network in the United States. Moreover, Facebook connections between countries reflect the patterns of international trade, and institution investments (Bailey et al., 2021; Kuchler et al., 2022).

In addition, there is a possible concern that Facebook connections might represent the populations differently across various countries. Duggan et al. (2015) prove that that U.S. Facebook users accurately represent the U.S. population. However, this is likely not the same for every country, especially countries with low internet coverage and penetrations. Therefore, I followed Bailey et al. (2021) and incorporate fixed effects for locations i and j in all models to account for differences in the average connectedness across locations and countries. This approach enables us to analyse the connectivity between two countries, while controlling for the probability of having Facebook friends in different countries for each location. In addition, I use internet users as instrument variable to address the potential concerns.

4.4.3 Control Variables

Following the research about deal formation and deal outcomes, I include control variables of VC investors, portfolio companies, and country characteristics which eventually influence deal formation, exit performance, and innovation outcomes.

To examine the role of social connectedness in deal formation, I follow control variables used in the research of Bottazzi et al. (2016), which examine how trust influence VC deal formation and success. I account for a variety range of country-pair variables and VC-PC pair variables to capture the investor-company level change.

I incorporate four control variables to account for the impact of national differences on deal formation: GDP differences, contiguity, legal systems, and language similarity. Following Bottazzi et al. (2016), I capture economic and geographic disparities between VC and PC countries through GDP differences, calculated as the log-transformed per capita GDP, and a contiguity indicator distinguishing neighbouring countries with sharing border from non-neighbouring countries without sharing border. Bottazzi et al. (2016) and Buchner et al. (2018) highlight the importance of geographic proximity in deal formation. Particularly, Buchner et al. (2018) demonstrate significantly lower investment returns for cross-border deals involving non-contiguous countries compared to contiguous ones. Furthermore, to control for transaction costs, I include variables for legal and linguistic similarities. Legal systems, extracted from La Porta et al. (1998), are classified as English, French, German, or Scandinavian origin law, with a binary indicator denoting differences between VC and PC countries (Chemmanur et al., 2016; Buchner et al., 2018). In addition, Tian and Wang (2014) illustrate that legal system matters for innovation performance, so I control the effect of legal system differences on investment outcomes. Language overlap, reflecting cultural and communication aspects, is measured through a binary variable indicating whether the same language is spoken in both countries (Dow and Karunaratna, 2006; Li et al., 2014).

I include variables to account for VC-PC pair characteristics, such as geographic distance, industry fit, and stage fit. Geographic distance, as noted by Li et al. (2014) and Sorenson and

Stuart (2001), increases information-gathering and monitoring costs, shaping VC decision-making. Industry and stage fit capture the alignment between VC investment styles and portfolio companies, reflecting the importance of specialization in cross-border VC investments. Chemmanur et al. (2016) highlight the role of industry-specific expertise in evaluating business viability, while Bottazzi et al. (2016) emphasize that companies are more likely to attract investments when they are aligned with the VC investors' strategic plan. Specialization impacts both VC decisions and investment outcomes.

Moreover, the performance of investments may be influenced by other factors. To address this, I first incorporate variables to account for VC attributes. According to previous literature, investment exits could be shaped by unobservable VC-specific characteristics. Following Bottazzi et al. (2008), I use the total capital under management by the venture capital firm at the end of sample period, to proxy for VC size. As Hochberg et al. (2007) suggested, larger VC firms possess more recourse, a broader pool of experts, conduct more thorough due diligence, and provide enhanced monitoring services, all of which significantly impact the outcomes of investment exits and innovation. Furthermore, I control for VC types, such as independent or corporate VCs. Hellmann and Puri (2002) and Nguyen et al. (2023) highlight that independent VC firms prioritize achieving maximizing financial returns, whereas corporate VC firms emphasize the strategic synergies investments can bring to their core operations. Consequently, the type of VC firms influence may influence investment exit outcomes and driving innovation.

Second, besides controlling for VC characteristics, I also account for deal-specific factors, including deal size, which reflects the amount of funding received by the portfolio company. Portfolio companies that receive greater funding are more likely to achieve successful exits and present a stronger innovation performance (Dai and Nahata, 2016). Additionally, Tian (2012) implies that a larger number of VC investors are more likely to exit through IPO or M&A relative to write-off. Hence, I include the number of VC investors investing in portfolio companies across all rounds. Furthermore, as outlined by Nguyen et al. (2023), I incorporate the total count of funding rounds to capture deal-specific attributes.

In addition, I also apply a set of fixed effects in the tests, particularly portfolio company and VC investor fixed effects. I use company characteristic controls such as the industry in which the company operates, classified based on subgroup 1 industries in Eikon. In addition, building on the approach of Li et al. (2014), I incorporate fixed effects for the financing stage it pursued, such as seed, start-up, early stage, or expansion, by including dummy variables for stage in the analysis. What's more, I code portfolio company nation, stage, industry, and investment year in fixed effects to capture the time-invariant and unobserved characteristics of the portfolio companies and cross-country differences. All tests are clustered by country pair.

4.5. Summary Statistics

In this section, I present the summary statistics of the two samples for examining H1 and other hypotheses in Table 2.1 and Table 2.3, respectively.

Table 2.1 provides summary statistics for potential deals in 2019. The initial dataset includes 3,265,037 cross-border VC-PC pairs, representing 1,289 cross-border VC investors and 2,533 portfolio companies, with 3,265,423 observations due to repeated deals. After excluding cases with missing SCI data for countries such as Russia, China, and Iran, the final sample consists of 2,587,898 observations. The dependent variable, DealHappen, is a binary indicator of whether a potential pairing leads to a transaction, with 0.18% of potential pairs culminating in actual deals. The primary independent variable, ln (SCI), has a mean of 8.83 and a standard deviation of 1.9, consistent with the dataset used by Kuchler et al. (2022).

Furthermore, the descriptive statistics indicate that 5% of country pairs in the sample are neighbours with shared borders, while the remainder are non-contiguous foreign countries. In addition, geographic distance is measured using two variables: the direct distance between countries and the distance between their capital cities, both averaging approximately 6,800 kilometres with a big spread. The log-transformed distance has a mean of 8.4 and a standard deviation of 1.05. These values are consistent with those reported by Buchner et al. (2018).

Approximately 52.98% of VC firms operate under legal systems different from those of portfolio companies, while 28.8% share a common language. The average GDP difference between VC and portfolio company countries is $2,376.09, indicating that most VCs are based in higher GDP per capita nations. On average, the industry fit is 38.77%, and the stage fit is 47.44%, consistent with Li et al. (2014), who observe that nearly half of the deals align with VC specialization. Moreover, Table 2.2 displays the correlation matrix, showing a high correlation between two geographic distance measures, for countries and capital cities. Therefore, only one measure is retained for further analysis. Additionally, DealHappen shows a negative correlation with geographic distance, confirming the presence of Home Bias, while its positive correlation with social connectedness supports Hypothesis 1.

[Table 2.1: Summary statistics]

[Table 2.2: Correlation matrix]

In addition, Table 2.3 represents the summary statistics of the sample consists of all realized cross-border VC investments in 1996-2021. There are 24,399 deals in total. Deleting observations with missing SCI, I end up with 19,377 observations in the final sample. The main dependent variables are success exits, number of patents, and number of citations to quantify the firm financial performance and innovation performance. As it is shown in Table 2.3, there are about 30% of the deals have successfully exits, aligning with previous research on exits performance (Li et al., 2014; Nahata et al., 2014). On average, portfolio companies produce 4 patents, and 25 citations from new patents, within 3 years of cross-border VC investments, consistent with the finding of Tian and Wang (2014). The mean of the primary independent variable, the natural logarithm of the Social Connectedness Index, is 8.54 with a standard deviation of 1.10. Geographic distance, measured as both the direct distance between countries and the distance between their capitals, shows similar statistics, with a mean natural logarithm of 8.3 and a standard deviation of 1.11.

[Table 2.3: Summary statistics]

Furthermore, similar to sample 1, I find that approximately half of the VC-PC pairs tend to have different legal origins and languages. The average internet user coverage across all countries is 62%, with a standard deviation of 22.98. Regarding VC characteristics, the mean natural logarithm of capital under management is $7.88 millions, as noted by Liu and Maula (2021). In addition, aligning with study by Nguyen et al. (2023), I find that while approximately 10% of VC investors in the sample are corporate venture capitalists, independent VC firms account for the majority of deals. For deal characteristics, the natural logarithm of the average investment in portfolio companies is $2.66 million, typically involving 4 to 5 VC investors across all rounds. The average number of financing round is 2. In addition, Table 2.4 demonstrations the correlation matrix of the main variables. It suggests that social connectedness is negative related with successful exit, and positively related with the number of citations, supporting hypothesis 2, and hypothesis 3.

[Table 2.4: Correlation matrix]

4.6. Empirical Tests and Methodology

This section examines the influence of social connectedness on VC investment choices and outcomes. I employ logit regression to assess the role of social connectedness on cross-border VC firms' deal selection decisions. Additionally, I use a logit model to examine the relationship between social connectedness and exit outcomes, and a Poisson regression to study its impact on innovation performance. Furthermore, I utilize instrumental variable in Heckman two stage regression to address potential endogeneity concerns.

4.6.1 Deal Formation

In this section, I examine Hypothesis 1, which proposes that greater social connectedness increases the likelihood of VC firm making an investment. I assess the effect of social connectedness on cross-border VC investments using a sample of all potential deals between VC firms and portfolio companies engaged in cross-border VC investments recorded in Eikon from January 2019 to December 2019.

I use the following equation to test the relation.

Equation 4: Baseline model for deal formation

$$\mathbf{DealHappen}_{i,j} = \boldsymbol{\alpha} + \boldsymbol{\beta}_1 \mathbf{ln(SCI)}_{i,j} + \boldsymbol{\beta}_2\ \mathbf{Z}_{\mathrm{i,j}} + \boldsymbol{\beta}_3 \mathbf{X}_{\ i} + \boldsymbol{\theta}_{\ \mathrm{j}} + \mathbf{v}_{\mathrm{j}}$$

Where the dependent variable, DealHappen, is a binary indicator that equals one if VC investor i invests in company j, and zero otherwise. The intercept term is represented by α. Ln (SCI) refers to the natural logarithm of the Social Connectedness Index between the countries of VC firm i and portfolio company j. The vector Z includes control variables at the investor-company country-dyad level, such as geographic distance, legal differences, shared borders, common language, and GDP difference. The vector X contains characteristics specific to VC firms, including stage fit and industry fit, to represent the proportion of deals the VC investor has made at the same financing stage or industry as the portfolio company. Portfolio company fixed effects, denoted by θ, are included to control for time-invariant and unobserved characteristics of the portfolio companies, such as industry and stage fixed effects. Moreover, following Bottazzi et al. (2016), I incorporate investee country fixed effects in the analysis. In addition, Bottazzi et al. (2016) also indicate that country fixed effects help control for country-specific factors, such as investment opportunities, the legal and institutional environment, and investor-friendliness. The SCI coefficient measures how deviations from the average connectedness to a company's home country influence the probability of VC investment. I cluster standard errors by country-dyad and report the results in Table 2.5 and Table 2.9.

[Table 2.5: Baseline 1.1 - Logit Regression]

Table 2.5 displays the Equation 4 estimation results using logit model to evaluate the impact of countries social connectedness on the probability of the deal formation. The results demonstrate that the coefficients for social connectedness are consistently positive and significant at the 1% level across all specifications. This strongly supports the Hypothesis 1 that social connectedness positively influences the probability of cross-border VC deal formation.

The estimated coefficients are not only statistically significant but also represents an economically substantial effect. In Column (1), I regress social connectedness on the dummy variable, DealHappen, in logit regression, and I find that there is a positive significant relationship between social connectedness and the likelihood of deal formation. In Column (2), I incorporate portfolio company fixed effects into regression. The coefficient of social connectedness remains consistently positively significant, demonstrating the robustness of the results even with the inclusion of portfolio company fixed effects. This result remains robust to controlling for VC firm and portfolio company characteristics. Furthermore, I test the relation of social connectedness with deal formation when adding control variables in Column (3), adding portfolio company fixed effect in Column (4), and adding portfolio company nation fixed effects in Column (5). The results are consistent with prior literature on institutional and crowdfunding investor behaviour (Kuchler et al., 2021; Peng and Zhang, 2024), showing that social connections are positive related with investment likelihood, and cross-border VCs are more likely to invest in countries with stronger social connections.

Furthermore, I find that the coefficient for geographic distance is negative and significant, exhibiting the home bias of VC investments, aligning with the results from Cumming and Dai (2010). Furthermore, I find that the estimated coefficient for stage fit is significantly positive, suggesting that specialization is a critical for VC deal formation (Chemmanur et al., 2016; Bottazzi et al., 2016). VC firms leverage their previous expertise in cross-border investments.

As shown in Column (5), the estimated coefficient for ln (SCI) is 0.3042, which suggests that one-unit increase in natural log transformed social connectedness between VC and PC countries, is associated with approximately a 35.55% increase in the odds of the deal formation between the pair. More importantly, I observe that adding controls and fixed effects does not impact the significance of social connectedness. All coefficients for ln (SCI) remain consistently positive and unchanged across all conventional significance levels. This indicates that social connectedness has a significant impact on deal formation. For instance: the ln (SCI) value between India and United States is 6.66, while it is 7.30 between India and United Kingdom. This one unit rise in social connectedness, assuming other variables remain the same, results in a 35.55% higher likelihood of forming a deal.

Moreover, I use probit regression estimate the probability of deal formation, with the results presented in Robustness. I observe the consistent and robust results as in Table 2.5. The estimated coefficients for social connectedness are positive and significant at all specifications.

Therefore, aligned with the prediction and previous literature about social connections, the results suggest that the probability of a cross-border VC firm participating in a deal significantly rises when the two countries involved share strong social connections. The findings support the hypothesis that cross-border VC investors are more likely to invest in portfolio companies that located in socially connected countries.

4.6.2 Success Exit

In this section, I test Hypothesis 2, predicting a negative relationship between social connectedness and success exit of cross-border VC investments. Analysing all realized cross-border deals in the period of 1996-2017, I define a successful exit as the portfolio company either going public or being acquired by the end of 2021, which allows a minimum of 5 years for the investment to exit. Otherwise, the investment is considered a failure. To analyse the impact of social connectedness on the likelihood of successful exits, I apply the dummy variable *'success'* as the dependent variable and employ the following equation to assess the relationship.

Equation 5: Baseline model for successful exit

$$\mathbf{SUCCESS}_{i} = \boldsymbol{\alpha} + \boldsymbol{\beta}_1 \mathbf{ln}\ (\mathbf{SCI})_{i,j} + \boldsymbol{\beta}_2\ \mathbf{Z}_{\mathbf{i,j}} + \boldsymbol{\beta}_3 \mathbf{X}_{i} + \boldsymbol{\beta}_4 \mathbf{W}_{j} + \boldsymbol{\theta}_{\mathbf{j}} + \mathbf{v}_{\mathbf{j}}$$

Similar to Equation 4, where ln (SCI) is the main independent variable, the vector Z includes control variables at the investor-company country-dyad level, the X captures the VC investors characteristics, and W contains deal characteristics. In addition, to control for time-invariant and unobserved characteristics of the portfolio companies, I incorporate portfolio company fixed effects in the model, represented by θ, involving industry, stage, and year fixed effects.

[Table 2.6: Logit]

I implement logit regressions in Equation 5 and report the empirical results in Table 2.6. The results reveal that the coefficient for ln (SCI) is negative and significant at the 1% level after adding control variables. This provides strong evidence in support of Hypothesis 2, suggesting that social connectedness reduces the likelihood of successful exits. Specifically, I regress social connectedness on the probability of successful exit in Column (1), and I add portfolio company industry, stage, and year fixed effects in Column (2). The results imply that social connectedness doesn't have a significant impact on deal performance. However, in Column (3), I add control variables of the investor-company country-dyad, VC investors, and deal characteristics, to account for country, investor, and deal heterogeneity. It is shown that the pseudo-R square increases from 6.88 % to 10.38%, which shows a significant role of the control variables in explaining the determinants of performance. Meanwhile, I find that the estimated coefficient for ln (SCI) is negative and significant at 1% level, indicating a significant negative impact of social connectedness on successful exits. Furthermore, I add portfolio company industry and financing stage fixed effects in Column (4) test, the coefficient for social connectedness remains negative and statistically significant at 1% level, shown as -0.763. From an economic perspective, this implies that one percentage increase in social connectedness between VC and PC countries results in a 7.63% decrease in the likelihood of a successful exit. Consistent with the findings of Gompers et al. (2016), the results report that the homophily reduces the probability of investment success.

In addition, the results indicate that the GDP difference is significantly positively associated with deal performance, suggesting that greater disparities in GDP per capita increase the likelihood of successful exits. Furthermore, consistent with Bottazzi et al. (2016) and Buchner et al. (2018), I find a shared language facilitates communication and has a positive impact on performance. Moreover, portfolio companies receiving larger size of investments and undergoing more financing rounds from VC investors demonstrate improved deal performance.

Furthermore, I employ probit regressions to analyse the marginal impact of social connectedness on the financial performance of portfolio companies. I display the results in robustness tests. It presents similar results as logit regression. After adding control variables, the estimated coefficient for ln (SCI) remains negative and statistically significant at the 1% level in Column (3). The results remain consistent and robust after incorporating portfolio company industry and financing stage fixed effects in Column (4). It demonstrates a negative and statistically significant relationship of social connectedness on successful exits.

Thus, both logit and probit regression results support the conjecture in Hypothesis 2, a negative relationship between social connectedness and successful exits. I discover that social connectedness deteriorates deal performance. Cross-border VC investors are less likely to achieve successful exits in portfolio companies located in socially connected countries.

4.6.3 Innovation Performance

In this session, I test the role of social connectedness in portfolio company innovation performance, measured by the number of patents and the number of citations in 3 years after cross-border VC investments, denoted as Y in the Equation 3 below. As suggested by prior studies (Cohn et al., 2022; Chen and Roth, 2024), Poisson regression is widely employed in econometric analysis for count data, such as innovation analysis. It offers more consistent and efficient estimates under broader conditions compared to logarithmic transformations. This approach is particularly effective for analysing patents and citations, as it appropriately captures the characteristics of innovation measures. Therefore, I utilize the Poisson pseudo-maximum likelihood estimator to address the truncation of patent and citation counts at zero. The regression is expressed in the following equations.

Equation 6: Baseline model for innovation

$$Y_{i,j} = \exp[\alpha + \beta_1 \ln\ (SCI)_{i,j} + \beta_2\ Z_{i,j}\ \ + \beta_3 X_{\ i} + \beta_4 W_j + \theta_{\ j}].\ \varepsilon_{i,j}$$

As before, where α is the intercept term, ln (SCI) is the main explanation variable, vector Z includes control variables at the investor-company country-dyad level, X and W captures characteristics specific to VC investors and deals, respectively. In addition, I incorporate θ, representing portfolio company fixed effects, involving industry, stage, and year fixed effects.

[Table 2.7: Baseline 3]

Table 2.7 presents Equation 6 estimated results of the role of social connectedness on innovation performance. The results illustrate that the coefficients for social connectedness on patent and citation counts are both positive and significant, indicating that social connectedness enhances the innovation performance of portfolio companies. Specifically, Column (1) shows the relationship between social connectedness and the number of patents, incorporating country, VC investor, and portfolio company control variables, along with the fixed effects. The coefficient is not only statistically significant at 5% level, but also exhibits a significant economic value. It shows that 10% higher social connectedness to a given foreign country on average, results in a 5% growth in the number of patents. In addition, the coefficient for social connectedness is 0.3008, which is significantly positive at 10% level in Column (2). It indicates that when social connectedness between the VC and portfolio company countries rises by one unit, the number of citations improves by 35.09%. These findings align with social network theories highlighting the role of social networks in facilitating knowledge recombination and innovation (Glaeser, 1999; Sorensor and Stuart, 2001; Choudhury, 2022)

In addition, I also observe that the coefficient for common border is positive and significant. This confirms the finding by Brown and Martinsson (2019) that reduced information asymmetry and low information costs encourage innovations. The coefficient for both LegalDiff and ln_geo_distcap are positive and significant. As suggested by Granovetter (2018), this is consistent with knowledge spillover effect and indicates that diverse information sources enhance innovation. Furthermore, the positive and significant coefficient for ln_pcreceive suggests that receiving more funding enables portfolio companies to generate both more patents and citation counts. The findings are consistent with Chahine et al. (2022) that increased funding thus facilitates greater R&D spending, ultimately enhancing innovation outcomes, as evidenced by the higher number of patents and citations.

These findings support Hypothesis 3, which predicts that greater social connectedness promote innovation. In other words, cross-border VCs fosters innovation by investing in socially connected portfolio companies.

4.6.4 IV & Heckman Two-Stage Regression: Internet Users

The previous results suggest that social connectedness significantly negative influence the successful exits probability. However, there might be some endogeneity issues in the relationship and cross-border VC decision making, such as some omitted variables that simultaneously increase a firm's likelihood of having higher social connectedness with PC countries and the probability of successful exits, thereby causing social connectedness endogenous. Although it is challenging to address the omitted variables problem and selection bias concern without doing a natural experiment, I implement two approaches to mitigate the potential concerns. First, I control for endogeneity in VC decision by the instrument variable approach. Second, I exploit the Heckman (1979) two-step regression to correct for selection biases.

As a valid instrumental variable should be correlated with VC cross-border investment decisions but not be correlated with the investment performance. Following Dai and Nahata (2016), I use the VC country's internet user coverage in the given year to construct the instrument variable. I estimate that a greater coverage of internet users is more likely to have a rich information environment, as well as more social connections to another country on Facebook. The increased internet user coverage facilitates information exchange and enhances awareness of investment opportunities in foreign markets, thereby increasing the likelihood of VCs engaging in cross-border investments. As the investment decision is made solely by VC investors and not by the entrepreneurial firm, the instrument variable satisfies the exclusion restriction criterion. Furthermore, I assume that the number of internet users has no direct effect on portfolio company performance, ensuring the validity of the instrument.

In Heckman two stage model, specifically, using all realized deals, in the first step, it is a probit regression to estimate the probability of cross-border VC investment (CBVC). In the second step, I assess how social connectedness affects the success of portfolio company exits, as shown in Equation 7.

Equation 7: Heckman two stage regression

$$\mathbf{CBVC}_i = \alpha + \beta_1 \mathbf{Instrument\ variable} + \beta_2\ \mathbf{Controls} + v_j \quad \mathbf{(1)}$$

$$\mathbf{SUCCESS}_i = \alpha + \beta_1 \ln\ (\mathbf{SCI})_{i,j} + \beta_2\ \mathbf{Controls} + v_j \quad \mathbf{(2)}$$

[Table 2.8: Heckman two stage]

I state the results in Table 2.8. It indicates that the instrumental variable is significantly and positively correlated with cross-border investment decisions, establishing its validity by meeting the relevance criterion. Moreover, the positive relationship between internet user coverage and cross-border VC investment formation aligns with the theoretical predictions and empirical evidence in Dai and Nahata (2016), suggesting that higher internet penetration strengthens international social connections and economic linkages. Furthermore, the coefficient for the inverse Mills ratio is found to be highly significant, confirming the presence of selection bias in the regression and controlling for endogeneity is important. Notably, after incorporating the inverse Mills ratio from the first stage into the second-stage regression, the estimates remain statistically significant and consistent with the results presented in Table 2.8 and Table 2.10. The results align with the expectation of a negative relation between social connectedness and the probability of success exits. This magnitude aligns with the findings presented by Nguyen et al. (2023) for portfolio investments.

4.7. Concluding Remark

With the trend of cross-border VC investments surging with the growth of the VC industry, this study draws on data from Eikon, Facebook, and Orbis-IP to empirically assess the impact of social connectedness between countries on cross-border VC investments. I examine deal formation, investment exits performance, and innovation outcomes of portfolio companies. Firstly, using counterfactual analysis on potential VC-PC pairs from 2019, I find that cross-border VCs are more likely to invest in companies from socially connected countries. Secondly, logit and probit regressions reveal that greater social connectedness negatively affects investment performance, as measured by successful exits. Specifically, a 1% increase in social connectedness between VC and PC countries leads to a 7.63% decrease in the likelihood of a successful exit. Last but not the least, I analyze portfolio company innovation and find that social connectedness enhances knowledge spillovers, thereby boosting innovation.

This study determines causality by utilizing a range of control variables along with fixed effects. Additionally, I employ the Heckman two-stage model, using the proportion of Internet users in VC countries as an instrumental variable to address potential endogeneity concerns such as omitted variables and selection bias. The results are robust and remain consistent. These findings provide meaningful understanding of how social connections between countries shape cross-border VC investment decisions and their outcomes. Moreover, the results illustrate the broader impact of social connectedness on international venture capital strategies and portfolio company success.

4.8. Appendix

Appendix A: Variable Definitions

Dependent variables:

DealHappen: A dummy variable that takes the value of one if the deal actually happened. The deal data are obtained from Eikon.

Success: A dummy variable that takes the value of one if the company has been exited via an IPO or acquisition by December 2021 and zero otherwise. The data are obtained from Eikon.

Patents: The number of patents that are applied and final granted for the investee company within 3 years after VC investments.

Citations: The number of citations received from the patents which are applied and final granted after 3 year of VC investments.

Independent variables:

Country characteristics:

scaled_sci: The number of Facebook connections between the headquarters' country of a VC firm and that of the portfolio company, adjusted by the product of the populations in both countries.

ln_sci: The natural logarithm of one plus the social connection index

gdpdiff: The difference (for each country pair) of the log-transformed per capita GDP, expressed in dollars in a given year. This variable is obtained from WDI.

Language (comlang_off): A dummy variable if people are speaking the same language in investee company country and investor country. This variable is set to one for domestic deals. The data are obtained from CEPII-Gravity.

LegalDiff: A dummy variable that takes the value of one if investor and company are located in countries with different legal origins and zero otherwise. I distinguish between Common law, French-origin civil law, German-origin civil law, and Scandinavian-origin civil law. The data are obtained from La Porta et al. (1998)

ln_geo_simpledis: The natural logarithm of one plus the kilometric distance between the two countries' capital cities. The data are obtained from CEPII-Gravity.

contig: A dummy variable that takes the value of one if the investor's and company's countries share a land border and zero otherwise (including domestic deals). The data are obtained from CEPII-Gravity.

cbvc: A dummy variable that takes the value of one if the investor and company are from different countries and zero otherwise

VC characteristics**:**

Industry fit: The percentage of the deals made by the venture capital investor in the same industry of the company

Stage fit: The percentage of the deals made by the venture capital investor in the same stage at which the company is financed

Independent VC: A dummy variable that takes the value of one if the venture capitalist defines itself as an independent venture firm and zero otherwise

ln_VC size: The natural logarithm of one plus the amount under management of the VC firm at the end of the sample period, in millions of current euros

ln_pcreceive: The natural logarithm of one plus the amount of funding received by the investee company.

number_vc: The number of VC investors investing in portfolio companies across all rounds.

RoundNumber: The total count of funding rounds.

VC age: The natural logarithm of one plus the age of the venture capital firm, measured in months at the end of the sample period.

CVC: A dummy variable that takes the value of one if the venture capitalist defines itself as an independent venture firm and zero otherwise.

Industry: A set of dummy variables for each company's industry.

Year: A set of dummy variables for investment year.

Stage: A categorical variable including Startup/Seed, Early Stage, Expansion, Later Stage, and Buyout/Acquisition.

Portfolio company: A set of investee company dummy variables.

Portfolio company nation: A set of investee country dummy variables.

Country_pair: investee and investor country pair

Appendix B: Tables

Table 2.1: Summary statistics

Variable	N	Mean	SD	Min	P25	Median	P75	Max
dealhappen	2,578,898	0.0018	0.0425	0.0000	0.0000	0.0000	0.0000	1.0000
ln_sci	2,578,898	8.8290	1.9084	4.2905	7.7385	8.3712	9.2942	19.7660
scaled_sci	2,578,898	64097.5200	705273.2000	72.0000	2294.0000	4320.0000	10874.0000	384000000.0000
contig	2,578,898	0.0568	0.2315	0.0000	0.0000	0.0000	0.0000	1.0000
Exports_comtrade_o	2,578,898	0.4658	4.4131	0.0000	0.0093	0.0330	0.1267	260.7905
ln_geo_simpledis	2,578,898	8.4294	1.0739	0.6907	7.8199	8.7261	9.2618	9.8921
dist	2,578,898	6728.9230	4450.9590	0.9951	2488.7010	6160.5590	10527.4000	19772.3400
ln_geo_distcap	2,578,898	8.4586	1.0424	0.6907	7.7544	8.7955	9.2553	9.8921
distcap	2,578,898	6821.4170	4461.0470	0.9951	2330.7990	6603.1820	10458.9200	19772.3400
LegalDiff	2,578,898	0.5298	0.4991	0.0000	0.0000	1.0000	1.0000	1.0000
Investee_legal_orgin	2,578,898	2.1322	0.5887	1.0000	2.0000	2.0000	2.0000	4.0000
Investor_legal_orgin	2,578,898	2.0782	0.6947	1.0000	2.0000	2.0000	2.0000	4.0000
GDP_diff	2,578,898	2376.0940	32012.6800	-110651.7000	-18746.2400	0.0000	22373.3100	115312.7000
WDI_GDPpercapita_Investor	2,578,898	47810.5000	21743.9400	1437.1660	40415.9600	46793.6900	65120.3900	116153.2000
WDI_GDPpercapita_Investee	2,578,898	45434.3500	23496.2300	840.4496	33673.7500	46793.6900	65120.3900	112621.8000
industry_fit	2,578,898	38.7719	27.8664	0.0279	16.9492	33.3333	50.0000	100.0000
stage_fit	2,578,898	47.4355	28.5915	0.1039	25.0000	43.0108	66.6667	100.0000
comlang_off	2,578,898	0.2880	0.4528	0.0000	0.0000	0.0000	1.0000	1.0000
stage_code	2,578,898	2.4236	0.9888	0.0000	2.0000	2.0000	3.0000	6.0000
industry_code	2,578,898	8.9424	3.5435	1.0000	7.0000	7.0000	12.0000	18.0000

Table 2.2: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)dealhappen	1								
(2)ln_sci	0.0145	1							
(3)contig	0.0075	0.0991	1						
(4)Exports_comtrade_o	-0.0034	-0.0084	-0.0215	1					
(5)ln_geo_simpledis	-0.0153	-0.7138	-0.4397	0.0431	1				
(6)ln_geo_distcap	-0.0155	-0.7353	-0.3964	0.0408	0.9946	1			
(7)LegalDiff	-0.0112	-0.4562	-0.1399	0.0238	0.2036	0.2124	1		
(8)GDP_diff	0.0036	-0.0794	0.0151	-0.056	0.0084	0.0066	-0.0295	1	
(9)comlang_off	0.0078	-0.0840	0.2640	0.0486	0.1711	0.1907	-0.5666	0.0415	1

Table 2.3: Summary statistics

	N	Mean	SD	Min	p25	p50	p75	Max
Main dependent variables								
success	19,377	0.2699	0.4439	0.0000	0.0000	0.0000	1.0000	1.0000
Patents	19,377	4.2589	70.3277	0.0000	0.0000	0.0000	0.0000	2860.0000
Citations	19,377	25.3528	264.9767	0.0000	0.0000	0.0000	0.0000	9267.0000
Main independent variables								
scaled_sci	19,377	11,356	28,533	130	2,439	5,261	10,448	825,540
ln_sci	19,377	8.5458	1.0996	4.8752	7.7998	8.5683	9.2543	13.6238
Distance variables								
geo_simpledis	19,377	6,424	4,492	60	1,911	5,917	10,856	19,586
geo_distcap	19,377	6,577	4,498	60	1,911	6,197	10,919	19,586
ln_geo_simpledis	19,377	8.2977	1.1897	4.1046	7.5560	8.6857	9.2925	9.8826
ln_geo_distcap	19,377	8.3635	1.1146	4.1046	7.5560	8.7320	9.2983	9.8826
Control variables								
LegalDiff	19,377	0.5339	0.4989	0.0000	0.0000	1.0000	1.0000	1.0000
gdpdiff	19,377	-0.3813	1.4096	-5.0799	-0.6247	-0.0762	0.2554	4.8620
comlang_off	19,377	0.4683	0.4990	0.0000	0.0000	0.0000	1.0000	1.0000
Internetusers	19,377	62.2373	22.9772	0.0131	46.5000	69.9000	79.2000	98.3236
ln_vcsize	19,377	7.8757	3.3162	0.0000	5.3176	7.5951	12.0050	12.0050
ln_pcreceive	19,377	2.6605	1.8518	0.0000	1.0986	2.6532	4.0775	9.2966
number_vc	19,377	4.1920	3.2133	1.0000	2.0000	3.0000	6.0000	25.0000
RoundNumber	19,377	1.7601	1.4408	1.0000	1.0000	1.0000	2.0000	17.0000
CVC	19,377	0.1048	0.3062	0.0000	0.0000	0.0000	0.0000	1.0000

Table 2.4: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)success	1.0000															
(2)Patents	0.0066	1.0000														
(3)Citations	0.0855	0.5228	1.0000													
(4)ln_sci	-0.0185	-0.0057	0.0245	1.0000												
(5)contig	0.0079	-0.0064	0.0432	0.5015	1.0000											
(6)ln_geo_distcap	0.0314	0.0167	-0.0287	-0.7180	-0.6448	1.0000										
(7)ln_geo_simpdis	0.0289	0.0166	-0.0303	-0.7017	-0.6702	0.9909	1.0000									
(8)LegalDiff	-0.0141	0.0341	0.0054	-0.1513	-0.2799	0.0311	0.0309	1.0000								
(9)gdpdiff	0.0189	0.0066	0.0318	0.3408	0.1546	-0.2000	-0.2065	0.0902	1.0000							
(10)comlang_off	-0.0048	-0.0315	-0.0022	0.1680	0.2575	0.0067	0.0023	-0.7834	-0.1009	1.0000						
(11)Internetusers	-0.1750	0.0077	-0.0377	-0.0106	0.0212	-0.0214	-0.0256	0.0276	-0.3300	-0.0548	1.0000					
(12)ln_vcsize	0.0551	0.0011	-0.0422	-0.2563	-0.1257	0.2278	0.2200	0.0163	-0.1697	0.0124	0.0364	1.0000				
(13)ln_pcreceive	0.0187	0.1344	0.0363	-0.0607	-0.0632	0.0568	0.0611	-0.0798	-0.0636	0.0984	0.0389	0.1508	1.0000			
(14)number_vc	-0.0182	0.0396	0.0088	-0.0254	0.0223	0.0268	0.0232	-0.0293	0.0065	0.0458	0.1417	0.0627	0.3400	1.0000		
(15)RoundNumber	0.0531	-0.0014	-0.0023	-0.0253	-0.0117	0.0125	0.0132	-0.0264	-0.0607	0.0279	0.0098	-0.0054	0.0613	0.0392	1.0000	
(16)CVC	-0.0309	-0.0092	-0.0096	-0.0838	-0.0437	0.0960	0.0965	0.0770	0.0554	-0.1036	0.0622	0.1040	-0.0784	0.0004	-0.0110	1.

Table 2.5: Baseline 1.1 – Logit Regression

This table reports logit regression estimates the probability of the deal happen. The sample includes all possible VC-portfolio company pairs in 2019 in the unit level of VC-PC pair. The dependent variables are *DealHappen*, which is a dummy variable that takes the value of one if the deal really happened and zero otherwise; *ln_sci* the natural logarithm of social connectedness index, which is the number of Facebook links between a VC firm's country and a portfolio company's country, scaled by the product of the number of Facebook users in their countries; *contig* is a dummy variable that takes the value of one if the investor's and company's countries share a land border and zero otherwise; *ln_geo_discap* is the natural logarithm of the distance between the pair countries capital cities; *LegalDiff* is a dummy variable that takes the value of one if investor and company are located in countries with different legal origins and zero otherwise; *GDP_Diff* is the difference of the per capita GDP of pair countries, expressed in dollars; *industry_fit* is percentage of deals that the VC investor invested in the same industry as the company; *stage_fit* is the proportion of deals that the VC investor invested at the same financing stage as the company; *comlang_off* is a dummy variable if people are speaking the same language in investee company country and investor country; Portfolio company fixed effect is a set of dummies for each company's industry and stage. Portfolio company nation fixed effect is added in test 5. Standard errors are clustered by country-dyad and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DealHappen	DealHappen	DealHappen	DealHappen	DealHappen
	(1)	(2)	(3)	(4)	(5)
ln_sci	0.2561***	0.2600***	0.1601***	0.1592***	0.3042***
	(0.0065)	(0.0599)	(0.0171)	(0.0618)	(0.0542)
contig			-0.4904***	-0.4952*	-0.3954
			(0.0765)	(0.2944)	(0.3117)
ln_geo_discap			-0.2555***	-0.2566***	-0.1279
			(0.0235)	(0.0933)	(0.0805)
LegalDiff			-0.2258***	-0.2148	-0.1963
			(0.0588)	(0.2062)	(0.1392)
GDP_diff			0.0000*	0.0000	-0.0000***
			(0.0000)	(0.0000)	(0.0000)
Industry_fit			-0.0088***	-0.0053***	-0.0054***
			(0.0008)	(0.0016)	(0.0016)
Stage_fit			0.0002	0.0025**	0.0022**
			(0.0007)	(0.0011)	(0.0010)
comlang_off			0.5199***	0.5306**	0.7427**
			(0.0549)	(0.2561)	(0.2981)
_cons	-8.6652***	-9.0403***	-4.7904***	-3.5111***	-5.4078***
	(0.0661)	(0.6043)	(0.3449)	(1.2349)	(1.2073)
Portfolio company FE		Yes		Yes	Yes
Portfolio company nation FE					Yes
N	2,578,898	2,578,898	2,578,898	2,578,898	2,578,898
Pseudo R2	0.0204	0.0218	0.0342	0.0384	0.0464

Table 2.3: Baseline 2 --- Logit regression

This table reports logit regression estimates the probability of the successful exit of cross-border VC investments. The sample includes all cross-border VC-portfolio company pairs from 1996-2018 in the unit level of deals. The dependent variables are *Success*, which is a dummy variable that takes the value of one if the company has been exited via an IPO or acquisition by December 2021 and zero otherwise; *ln_sci* the natural logarithm of social connectedness index; *contig* is a dummy variable that takes the value of one if the investor's and company's countries share a land border and zero otherwise; *LegalDiff* is a dummy variable that takes the value of one if investor and company are located in countries with different legal origins and zero otherwise; *gdpdiff* is the difference of the two countries natural logarithm of per capita GDP, expressed in dollars in a given year; *comlang_off* is a dummy variable if people are speaking the same language in investee company country and investor country; *ln_vcsize* is the natural logarithm of one plus the amount under management of the venture capital firm at the end of the sample period, in millions; *ln_pcreceive* is the natural logarithm of total investments received by the portfolio company; *number_vc* is the number of VC firms investing in portfolio companies across rounds; *RoundNumber* is the number of financing rounds; *CVC* is a dummy variable that takes the value of one if the venture capitalist defines itself as an independent venture firm and zero otherwise; and the portfolio company's industry classification is based on subgroup 1 industries in VentureXpert. Standard errors are clustered by country-dyad and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Success	Success	Success	Success
	(1)	(2)	(3)	(4)
ln_sci	0.0140	-0.0078	-0.0727***	-0.0763***
	(0.0424)	(0.0340)	(0.0273)	(0.0288)
contig			0.0787	0.0985
			(0.1036)	(0.1033)
legalDiff			0.0281	0.0570
			(0.0869)	(0.0890)
gdpdiff			0.0608***	0.0370**
			(0.0151)	(0.0164)
ln_geo_discap			-0.0314	-0.0340
			(0.0391)	(0.0399)
comlang_off			0.2341***	0.2576***
			(0.0892)	(0.0906)
ln_vcsize			-0.0032	-0.0019
			(0.0070)	(0.0072)
ln_pcreceive			0.3075***	0.3034***
			(0.0279)	(0.0279)
number_vc			-0.0056	-0.0110
			(0.0151)	(0.0149)
RoundNumber			0.1090***	0.0806***
			(0.0187)	(0.0176)
CVC			0.0519	0.0298
			(0.0529)	(0.0540)
_cons	-1.0394***	-1.7549***	-0.3393	-1.2974**
	(0.3388)	(0.4445)	(0.5523)	(0.6028)
Industry FE		Yes		Yes
Year FE		Yes	Yes	Yes
Stage FE		Yes		Yes
N	19,377	19,377	19,377	19,377
Pseudo R2	0.0001	0.0688	0.1038	0.1185

Table 2.4: Baseline 3 --- Poisson regression

This table reports poisson regression estimates the relation between social connectedness and innovation outcomes. The sample includes all cross-border VC-portfolio company pairs from 1996-2018 in the unit level of deals. The dependent variables are *Patents* and *Citations*, which are the number of patents and number of citations received within 3 years after VC investments; *ln_sci* the natural logarithm of social connectedness index*; contig* is a dummy variable that takes the value of one if the investor's and company's countries share a land border and zero otherwise; *LegalDiff* is a dummy variable that takes the value of one if investor and company are located in countries with different legal origins and zero otherwise; *gdpdiff* is the difference of the two countries natural logarithm of per capita GDP, expressed in dollars in a given year; *comlang_off* is a dummy variable if people are speaking the same language in investee company country and investor country; *ln_vcsize* is the natural logarithm of one plus the amount under management of the venture capital firm at the end of the sample period, in millions; *ln_pcreceive* is the natural logarithm of total investments received by the portfolio company; *number_vc* is the number of VC firms investing in portfolio companies across rounds; *RoundNumber* is the number of financing rounds; *CVC* is a dummy variable that takes the value of one if the venture capitalist defines itself as an independent venture firm and zero otherwise; and the portfolio company's industry classification is based on subgroup 1 industries in VentureXpert. Standard errors are clustered by country-dyad and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Patents	Citations
	(1)	(2)
ln_sci	0.5000**	0.3008*
	(0.2499)	(0.1541)
contig	2.1115**	0.9740
	(0.8864)	(0.6136)
LegalDiff	1.0607**	0.6076
	(0.4170)	(0.3728)
gdpdiff	0.1200	0.1535
	(0.1152)	(0.0999)
ln_geo_distcap	0.7416**	0.2281
	(0.2927)	(0.2426)
comlang_off	-0.6363	-0.0280
	(0.6354)	(0.3752)
ln_vcsize	-0.0396	-0.1602*
	(0.0954)	(0.0933)
ln_pcreceive	0.8499***	0.5800**
	(0.1127)	(0.2621)
number_vc	-0.1634	0.0751
	(0.2370)	(0.3258)
RoundNumber	-0.1022	-3.4793
	(1.1061)	(0.8262)
CVC	-0.0067	-0.4001
	(0.7449)	(0.6524)
_cons	-16.5539***	-6.8679*
	(5.3830)	(3.6791)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Stage FE	Yes	Yes
N	19,377	19,377
Pseudo R2	0.6901	0.5589

Table 2.5: IV& Heckman two stage regressions

This table presents the results of IV & Heckman Two Stage estimations using 3-year window. The sample includes all VC-portfolio company pairs from 1996-2018 in the unit level of deals. The first column shows the first stage results, estimating the probability of a cross-border VC investments, and the second column presents the second stage results, testing the likelihood of the successful exits. The dependent variables are *CBVC* and *Success*, which are a dummy variable of cross-border VC investments, and a dummy variable that takes the value of one if the company has been exited via an IPO or acquisition by December 2021 and zero otherwise, respectively; *ln_sci* the natural logarithm of social connectedness index*; contig* is a dummy variable that takes the value of one if the investor's and company's countries share a land border and zero otherwise; *LegalDiff* is a dummy variable that takes the value of one if investor and company are located in countries with different legal origins and zero otherwise; *gdpdiff* is the difference of the two countries natural logarithm of per capita GDP, expressed in dollars in a given year; *comlang_off* is a dummy variable if people are speaking the same language in investee company country and investor country; *ln_vcsize* is the natural logarithm of one plus the amount under management of the venture capital firm at the end of the sample period, in millions; *ln_pcreceive* is the natural logarithm of total investments received by the portfolio company; *number_vc* is the number of VC firms investing in portfolio companies across rounds; *RoundNumber* is the number of financing rounds; *CVC* is a dummy variable that takes the value of one if the venture capitalist defines itself as an independent venture firm and zero otherwise; and the portfolio company's industry classification is based on subgroup 1 industries in VentureXpert. Standard errors are clustered by country-dyad and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. LR chi2 is reported for the first stage probit estimation.

	CBVC	Success
	(1)	(2)
Internetusers	0.0123***	
	(0.0018)	
Ln_sci		-0.0130***
		(0.0044)
1.contig	0.1466	0.0098
	(0.0017)	(0.0140)
Ln_geo_distcap	1.4023***	-0.0088
	(0.0389)	(0.0054)
1.LegalDiff	0.7934	-0.0053
	(0.0010)	(0.0146)
gdpdiff	-0.4177***	0.0059**
	(0.0416)	(0.0027)
1.comlang_off	0.7697	0.0313**
	(0.0012)	(0.0143)
ln_vcsize	-0.0671***	-0.0013
	(0.0073)	(0.0010)
ln_pcreceive	-0.0857***	0.0519***
	(0.0179)	(0.0026)
number_vc	-0.0285**	-0.0001
	(0.0112)	(0.0015)
RoundNumber	0.0694***	0.0169***
	(0.0151)	(0.0025)
1.CVC	0.0718	0.0070
	(0.0665)	(0.0103)
/mills		-0.0190*
lambda		(0.0103)
_cons	-12.8176***	0.3058***
	(0.5542)	(0.0889)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Stage FE	Yes	Yes
N	98,791	98,791

Appendix C: Robustness

Table 2.6: Baseline 1.2 – Probit Regression

This table present probit regression estimates the probability of the deal happen. The sample includes all possible VC-portfolio company pairs in 2019 in the unit level of VC-PC pair. The dependent variables are *DealHappen*, which is a dummy variable that takes the value of one if the deal really happened and zero otherwise; *ln_sci* the natural logarithm of social connectedness index, which is the number of Facebook links between a VC firm's country and a portfolio company's country, scaled by the product of the number of Facebook users in their countries; *contig* is a dummy variable that takes the value of one if the investor's and company's countries share a land border and zero otherwise; *ln_geo_discap* is the natural logarithm of the distance between the pair countries capital cities; *LegalDiff* is a dummy variable that takes the value of one if investor and company are located in countries with different legal origins and zero otherwise; *GDP_Diff* is the difference of the per capita GDP of pair countries, expressed in dollars; *industry_fit* is percentage of deals that the VC investor invested in the same industry as the company; *stage_fit* is the proportion of deals that the VC investor invested at the same financing stage as the company; *comlang_off* is a dummy variable if people are speaking the same language in investee company country and investor country; Portfolio company fixed effect is a set of dummies for each company's industry and stage. Portfolio company nation fixed effect is added in test 5. Standard errors are clustered by country-dyad and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	DealHappen	DealHappen	DealHappen	DealHappen	DealHappen
	(1)	(2)	(3)	(4)	(5)
ln_sci	0.0808***	0.0820***	0.0510***	0.0511**	0.1027***
	(0.0021)	(0.0199)	(0.0057)	(0.0204)	(0.0202)
contig			-0.1737***	-0.1739*	-0.1406
			(0.0266)	(0.0982)	(0.1049)
ln_geo_discap			-0.0928***	-0.0924***	-0.0475
			(0.0084)	(0.0316)	(0.0292)
LegalDiff			-0.0779***	-0.0749	-0.0581
			(0.0195)	(0.0681)	(0.0483)
GDP_diff			0.0000**	0.0000	-0.0000***
			(0.0000)	(0.0000)	(0.0000)
Industry_fit			-0.0030***	-0.0019***	-0.0019***
			(0.0003)	(0.0006)	(0.0006)
Stage_fit			0.0000	0.0009**	0.0008**
			(0.0002)	(0.0004)	(0.0003)
comlang_off			0.1703***	0.1736**	0.2526**
			(0.0187)	(0.0862)	(0.1019)
_cons	-3.6477***	-3.7584***	-2.3118***	-1.8433***	-2.5075***
	(0.0208)	(0.1928)	(0.1183)	(0.4084)	(0.4252)
Portfolio company FE		Yes		Yes	Yes
Portfolio company nation FE					Yes
N	2,578,898	2,578,898	2,578,898	2,578,898	2,578,898
Pseudo R2	0.0201	0.0215	0.0339	0.0381	0.0454

Table 2.7: Baseline 2 --- Probit regression

This table reports probit regression estimates the probability of the successful exit of VC investments. The sample includes all cross-border VC-portfolio company pairs from 1996-2018 in the unit level of deals. The dependent variables are *Success*, which is a dummy variable that takes the value of one if the company has been exited via an IPO or acquisition by December 2021 and zero otherwise; *ln_sci* the natural logarithm of social connectedness index*;* *contig* is a dummy variable that takes the value of one if the investor's and company's countries share a land border and zero otherwise; *LegalDiff* is a dummy variable that takes the value of one if investor and company are located in countries with different legal origins and zero otherwise; *gdpdiff* is the difference of the two countries natural logarithm of per capita GDP, expressed in dollars in a given year; *comlang_off* is a dummy variable if people are speaking the same language in investee company country and investor country; *ln_vcsize* is the natural logarithm of one plus the amount under management of the venture capital firm at the end of the sample period, in millions; *ln_pcreceive* is the natural logarithm of total investments received by the portfolio company; *number_vc* is the number of VC firms investing in portfolio companies across rounds; *RoundNumber* is the number of financing rounds; *CVC* is a dummy variable that takes the value of one if the venture capitalist defines itself as an independent venture firm and zero otherwise; and the portfolio company's industry classification is based on subgroup 1 industries in VentureXpert. Standard errors are clustered by country-dyad and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Success	Success	Success	Success
	(1)	(2)	(3)	(4)
ln_sci	0.0086	-0.0053	-0.0447***	-0.0453***
	(0.0261)	(0.0203)	(0.0160)	(0.0167)
contig			0.0502	0.0590
			(0.0608)	(0.0600)
legalDiff			0.0223	0.0385
			(0.0510)	(0.0518)
gdpdiff			0.0335***	0.0192**
			(0.0090)	(0.0097)
ln_geo_discap			-0.0203	-0.0212
			(0.0227)	(0.0231)
comlang_off			0.1470***	0.1597***
			(0.0524)	(0.0526)
ln_vcsize			-0.0023	-0.0017
			(0.0041)	(0.0042)
ln_pcreceive			0.1775***	0.1750***
			(0.0171)	(0.0169)
number_vc			-0.0014	-0.0046
			(0.0091)	(0.0089)
RoundNumber			0.0663***	0.0497***
			(0.0112)	(0.0107)
CVC			0.0353	0.0194
			(0.0311)	(0.0317)
_cons	-0.6416***	-1.0262***	-0.1893	-0.7941**
	(0.2089)	(0.2574)	(0.3251)	(0.3515)
Industry FE		Yes		Yes
Year FE		Yes	Yes	Yes
Stage FE		Yes		Yes
N	19,377	19,377	19,377	19,377
Pseudo R2	0.0001	0.0687	0.1032	0.1180

Chapter 5: Climate Risks and Cross-border VC Investments

Abstract

This study investigates the impact of environmental factors on VC investment behaviour and performance. Integrating climate risk indicators from multiple data sources, this study assesses the role of climate risk in shaping cross-border VC investment decisions and outcomes. I find that due to salience bias, VCs from high climate risk country are more likely to invest cross-border. In addition, physical risks and transition risks reduce the likelihood of successful exits for cross-border VC investments. Moreover, stacked difference-in-differences (DiD) strategy, Heckman two stage, Cox hazard model are used to address endogeneity and ensure robust causal inference. Results are consistent and robust using alternative proxies and various tests. The findings provide new insights into the relation between climate risk and cross-border VC activity, demonstrating the importance of environmental considerations in cross-border investment strategies and outcomes.

5.1. Introduction

Climate change and its impact are increasingly acknowledged and concerned across the world. Intergovernmental Panel on Climate Change assessment report (IPCC, 2023) demonstrates that there are more frequent and severe climate extremes across global systems in recent years, resulting in substantial harm and measurable losses to both nature and people. Capital market participants have increasingly recognized the risk of exposure to climate changes and adverse financial consequences, such as raising cost of lending and financing for firms operating in high-risk regions (Huang et al.,2022); reduced returns of carbon-intensive stocks during abnormal warm periods (Choi et al., 2020); and declined market valuations of rain-sensitive firms in excessive rainfall weathers (Rao et al., 2022). Correspondingly, corporates adjust their strategies with climate change risks, such as more cash holdings to build financial slack and resilience to climatic threats (Nguyen and Phan, 2020; Ginglinger and Moreau, 2023), and institutional investors consider climate risks as financially significant in their investment decisions (Krueger et al., 2020).

Moreover, with the growing recognition of climate-related risk, recent studies generally decompose climate risks into physical risk and transition risk. Physical risk captures the direct economic losses arising from climate-related disasters and environmental shocks, which disrupt operations, reduce profitability, and increase financial constraints (Zhang et al., 2018; Hong et al., 2019; Huang et al., 2022). Investors respond by pricing such risks into financing terms and reducing exposure to high-risk regions (Huang et al., 2022; Huang et al., 2024). Transition risk, in contrast, reflects the uncertainty generated by the shift toward a low-carbon economy, including regulatory change, technological adjustment, and evolving consumer and social preferences (Bolton and Kacperczyk, 2023). These risks also affect investor behaviour, as climate policy exposure is associated with higher required returns, valuation pressure, and adjustments in firms' capital structure and investment decisions (Nguyen and Phan, 2020; Ilhan et al., 2021; Hsu et al., 2023).

Although investors are aware of climate risk, their perceived exposure may not fully align with the underlying realised risk. Literature has recorded salience bias in the decision making, shown as the recognition of climate risks increases substantially after individual experiencing and direct expose to climate-related events and leads to subsequent adjustments in investments.

For example, individuals become more convinced of climate change when temperatures deviate from historical norms and they are more inclined to donate to global warming charities (Li et al., 2011); Similarly, episodes of air pollution trigger a temporary surge in the health insurance purchase (Chang et al., 2018), and heatwaves raise public concerns about global warming, evidenced by increased Google searches, and prompt retail investors to divest from carbon-intensive firms (Choi et al. 2020). Similar in corporate finance, climate shocks prompt managers precautionary and governance responses. Dessaint and Matray (2017) discover that following hurricanes, affected managers consequently increase cash reserves and explicitly highlight hurricane related risks in their 10-K and 10-Q fillings, regardless any changes in actual hurricane risk. Therefore, it is vital to understand the how investors respond to climate change, and whether such responses reflect systematic biases in decision making.

VC investors have been critical investors of economic growth and an increasingly important asset class. Although venture capital investments involve substantial exposure to both systematic and idiosyncratic risks (Gornall and Strebulaev, 2020; Korteweg and Sorensen, 2010), VC funds have consistently achieved superior financial returns exceeding those of public markets, even after accounting for fees (Harris et al., 2014). In addition, VC-backed firms exhibit superior efficiency, shown as higher likelihood of going public or being acquired than non-VC backed companies (Chemmanur et al., 2011), and VCs continue to foster firm growth beyond the IPO stage (Amini et al., 2022). As VCs expand rapidly in their domestic markets, the markets start to be saturated, leading to diminishing returns for VC investors. Notably, substantial capital inflows into the North American VC industry in the late 1990s resulted in decreased profitability relative to previous levels (Harris et al., 2014). Consequently, limited domestic opportunities motivated venture capitalists to expand globally, leading to a marked rise in cross-border VC investments (Buchner et al., 2018). VCs initially emerged in the United States and later expanded to the UK, Western Europe, and Japan. Simultaneously, regulatory reforms in numerous developing economies, such as Singapore and Hong Kong, enhanced their investment potential, increasing the perceived availability of viable investment opportunities for VC firms (Gompers and Lerner, 1998; Wright et al., 2005). Besides the information and uncertainties when investing domestic, cross-border VCs also face more challenges induced from geographic, cultural, institutional differences, which is also referred as liabilities of foreignness (LOF) (Zaheer, 1995). Consequently, cross-border VCs implement special strategies to overcome the challenges and LOF. Cross-border VCs are more likely to invest in countries with developed stock markets and stringent legal protections to reduce information asymmetry (Dai et al., 2012), and they monitor companies with more rounds and small investment size each round (Tian, 2011).

Although VC investors is critical for firm development and growing attention on climate change risks, there is limited research exploring the relation between VC investors on climate risks. Huang et al. (2024) find that VCs incorporate climate risk into investment decisions and are less likely to invest in disaster-affected regions, which exhibit lower chances of successful exits and shorter IPO timelines. Furthermore, unlike traditional VCs, impact investors derive nonpecuniary utility, aiming to generate social and environmental benefits alongside financial returns, defined by Global Impact Investing Network (GIIN). However, evidence suggests underperformance relative to traditional VCs. Barber et al. (2021) report that impact funds earn 4.7 percentage points lower IRRs, while Jeffers et al. (2024) show weaker performance against market beta. Although socially conscious investors accept lower returns for sustainable investments, the realized impact remains marginal. Heeb et al. (2023) show no significant premium for sustainable investments. Similarly, Berk and van Binsbergen (2025) argue that the effect of impact funds on the cost of capital is too small to influence real investment decisions and drive corporate change.

Despite the extensive evidence on how climate events reshape beliefs, and investor strategies, the relation between climate risk and cross-border venture capital investments has not been thoroughly explored. This study therefore seeks to fill that gap by empirically assessing how climate risk influences cross-border VC selection and post-investment outcomes. I investigate whether cross-border VCs adjust their investment allocation in response to heightened local climate risk and if so, how this affects their portfolio firms' subsequent performance. I speculate that VCs from high climate risk countries are more likely to invest cross-border, due to high perceived risks and salience bias.

In addition, I examine how climate risks, specifically, physical risk and transition risk affect investment exit outcomes. Previous studies have divided climate change risks into physical risks and transition risks (Lamperti et al., 2019; Venturini, 2022). Physical risks capture the adverse effects of climate and weather-related events on firms, supply chains, and society (Huang et al., 2024). Transition risks reflect uncertainty firms face in adapting to a low-carbon economy and the evolving investor expectations around this shift (Bolton and Kacperczyk, 2023). Therefore, in the second part of the study, I examine the influence of both types of climate change risks on cross-border VC investments outcomes.

To test the hypothesis, I draw on VC deal data from Refinitiv Eikon starting from 1996 to 2021, and I track investment performance until 2025. The primary measure of physical climate risk is Global Climate Risk Index (CRI) from Germanwatch (Eckstein et al., 2021), which quantifies country-level economic losses from extreme weather. In addition, I incorporate the Notre Dame Global Adaptation Initiative (ND-GAIN) indices covering both physical risks and transition risks. In this study, I examine the role of climate risk in cross-border VC investments selection and financial performance. I begin by estimating how home-country climate risk affects the VC firm invests internationally. Using probit regression, I find that higher home-country climate risk significantly increases the likelihood of cross-border VC deployment. Furthermore, I examine the influence of physical risks and transition risks on cross-border investments exits performance. I conduct probit regression of successful exits on physical risks and transition risks, discovering that physical risks reduce successful exits rates, while readiness capacity promotes successful exits, which also indicates a lower transition risk.

To further validate these results, I conduct more robustness tests and alternative measurements in further tests. I employ stacked difference-in-differences (DiD) identification to mitigate endogeneity issues, such as other factors influence investment decisions. I construct clean control groups with heatwave events in each cohort, and then I stack all cohorts together to conduct OLS regression on stacked dataset, assess how climate risks, such as heatwave influence the cross-border investments portfolio weights of VC investors. I observe consistent results, that VCs experience high climate risks are more likely to invest cross-border and increase cross-border investments weight. I acknowledge the possibility of omitted or unobserved factors that simultaneously affect climate risk and investment outcomes, which could bias the estimates. To mitigate these concerns, I pursue two complementary strategies. First, I use instrument variable, population density for climate risk, which is highly correlated with the exposure to extreme weather but plausibly exogenous to firm performance. Second, I employ a Heckman two-stage procedure to mitigate selection bias in investments. the results are consistent with previous findings, indicating transition risks are more salient and significant to investments performance. Furthermore, I apply cox hazard model to examine the determinates of VC successful exits, especially how climate-related physical risks affect investment outcomes. I find consistent results, showing that higher physical risk reduces the likelihood of successful exits, and delay the exits time. In addition, I use alternative proxies for climate risk, *CRI Rank*, and lagged climate risk indicators, and the results are consistent with the primary results, and confirming the robustness of the findings.

This study contributes to the general literature on climate finance, especially investor response about climate risk. Previous literatures report the investors recognize climate change risks on economic and financial significance (Krueger et al., 2020; Stroebel and Wergler, 2021). In response to tightening environmental policies, carbon-intensive firms face higher protection costs and subsequently relocate production outside of policy affected area (Ilhan et al., 2021; Bartram et al., 2022); mutual fund managers and retail investors systematically reduce their holdings in carbon-intensive stocks (Choi et al., 2020; Angelis et al., 2022; Ceccarelli et al., 2024), and endorse an environmental proposal (Fich and Xu, 2025). At the same time, investors demand a premium for bearing carbon-emission and tail-risk exposures, as reflected in higher option-implied uncertainty and wider credit spreads for firms with environmental concerns (Chava, 2014; Huang et al., 2022; Bolton and Kacperczyk, 2021; Kruttli et al., 2025). On corporate governance, elevated climate risk drives firms to hoard cash and deleverage to buffer against adverse outcomes (Huang et al., 2018; Ginglinger and Moreau, 2023); and customers are more likely to terminate supplier relationships as increasing physical climate exposure of suppliers. Although the growing body of evidence on how climate volatility influence firms and financial market participants decisions, a few research studying about how VC investors react to climate risks. Huang et al. (2024) find that reduced VC investments in natural disaster zones in US. However, whether cross-border VCs react on their international portfolio allocations concerning about climate risks is still unknown. This study aims to fill this gap by assessing both the propensity for cross-border VC investments and their subsequent performance outcomes.

This research also relates to a strand of cross-country literatures that focus on understanding of climate related behaviours. For example, high governance institutions, measured by strong civil liberties and political rights, boost firms' CSR performance (Cai et al., 2016), and low uncertainty avoidance encourages VC cleantech investments (Cumming et al., 2016), whereas less inclusive political systems command higher carbon risk premia (Bolton and Kacperczyk, 2023). Cultural and social expectations amplify these institutional pressures: investors from communities with strong E&S values drive greater CSR adoption (Dyck et al., 2019), especially in individualistic or devout societies where climate risk more strongly spurs CSR

(Ozkan et al., 2023), and civil-law jurisdictions further encourage sustainable corporate practices (Zhang, 2024). In addition, firms in low-income countries are more vulnerable to supply chain disruptions when natural disasters strike (Hong et al., 2019; Pankratz and Schiller, 2024). Policy frameworks play a pivotal role in shaping corporate environmental outcomes: higher emission taxes spur significant R&D investments (Brown et al., 2022), and subsidies in one jurisdiction catalyse broader innovation by multinational firms (Gerarden, 2023). However, stringent environmental regulations can weaken the link between green financing and performance unless supported by strong shareholder protections (Yan et al., 2021), while uncertainties, whether from climate volatility, economic policy shifts, or political instability, deter long-term sustainability investments (Jia and Li, 2020). Building on this body of work, this study makes three key contributions. First, this study is the first to examine how heightened home-country climate risk reshapes cross-border venture-capital allocations, advancing beyond prior research on domestic CSR and cleantech investments to explore VCs' international portfolio choices. Second, by linking exogenous variation in natural-disaster exposure, using CRI, to subsequent firm outcomes, I shed new light on the downstream effects of climate-driven capital reallocation, specifically, how shifting investments toward lower-risk jurisdictions affects portfolio companies' growth and resilience. Finally, I deploy a rigorous identification strategy, using instrumental-variable corrections for potential endogeneity, to isolate the causal impact of local climate risk on both VC deal selection and firm performance. In doing so, I integrate insights from institutional, cultural, and policy literatures to offer the first comprehensive analysis of climate risk's role in cross-border VC dynamics and its implications for sustainable entrepreneurship.

The reminder of this chapter proceeds as follow. Section 2 discusses the relevant literature and develops the hypotheses. Section 3 presents the database and sample selection process. Section 4 demonstrates the constructions of the variables, while Section 5 illustrates summary statistics. Section 6 provides the empirical tests and methodology, and Section 7 reports robustness tests, followed by conclusions in Section 8. Section 9 is appendix, including variables definitions and tables mentioned in the chapter.

5.2. Literature Review and Hypothesis Development

In this section, I review literature on climate finance, updating beliefs' economic impact, and climate risk management by VC investors, and develop three hypotheses for further testing.

5.2.1 Investor Rising Recognition of Climate Risk

An agreement between scholars has growing that human activity accelerates climate change, such as deforestation, rainforest degradation, and then leads to decreased biodiversity, diminishing valuable service provided by natural, such as carbon storage, atmospheric cleansing, soil formation, and freshwater filtration (Cohen and Winn, 2007). At the same time, investors have increasingly recognized the risks of climate change and are directing capital markets toward low-carbon and sustainable investments.

Giglio et al. (2025) indicate that financial academics, professionals, and policymakers believe climate risks are financially significant and investors with high ESG awareness tend to have more actual ESG holdings. In addition, institutional investors evaluate climate risks in investments and long-term investors choose to engage in risk management over divestments (Krueger et al., 2020). Specifically, institutional investor pressure through mechanisms such as carbon pricing, carbon tax, and targeted subsidies, proves the most effective drivers of corporate climate actions (Stroebel and Wergler, 2021). Moreover, investors with stronger belief in environment and social issue further guide companies toward sustainable growth in corporate governance. Dyck et al. (2019) indicate that investors, who are from country where environmental and social priorities are deeply embedded, encourage companies adopt more extensive CSR activities, and Cohen et al. (2023) report that institutional investors' increased demand for climate-related data prompts firms to enhance their disclosures and commit to reducing subsequent carbon emissions.

Previous studies show that climate change risks are divided into physical risks and transition risks. Physical risks are the physical damage on firm assets, company operations, society, and supply chains. Transition risks refer to all possible uncertainties coherent with a path to a low-carbon economy (Venturini, 2022). Therefore, I review how investors and companies incorporate physical risks and transition risks in their decisions. First of all, rising physical risks elevate both operating and financing costs, shown as higher cost of capital, higher borrowing expenses, and increased required returns. Chava (2014) indicates that lenders charge a significant higher interest rate on bank loans issued to firms with environmental concerns, such as hazardous chemicals, intensive emissions, and climate change concerns. In addition, such firms have lower institutional ownership and fewer banks participates in their loan syndicate than firms without such concerns. Furthermore, the rising cost of capital incentive for the carbon-intensive companies to reduce firms carbon emissions (Angelis et al., 2022) and mandatory carbon disclosure reduce the cost of capital (Bolton and Kacperczyk, 2021). Besides the increased cost of lending and financing, investors require compensations for high exposure of carbon emission exposure, such as carbon premia, shown in stock prices (Bolton and Kacperczyk, 2021; Bolton and Kacperczyk, 2023). Sautner et al. (2023a) find that market participants price climate-related risks and opportunities in stocks, and investors who buy stocks with higher climate change exposure demand an ex-ante risk premium; Hsu et al. (2023) show that high-emission firms earn higher risk premia; and high climate risk leads to a negative stock price (Barnett, 2023). Therefore, investor further adjust portfolio accordingly. After the release of Morningstar's novel carbon risk metrics in April 2018, mutual funds labelled as "low carbon" experienced a significant increase in investor demand, especially those with high risk-adjusted returns (Ceccarelli et al., 2024).

Secondly, transition risk arises from evolving climate policies, such as carbon taxes, cap-and-trade schemes, or emission limits, which influence both investor behaviour and corporate decision making. Climate-conscious institutional investors actively engage with portfolio company management to promote risk transparency and encourage climate risks disclosures, driving further improvements (Ilhan et al., 2023); families sign the Principles for Responsible Investment (PRI) have significantly lower portfolio emissions and further they receive increased fund flows (Humphrey and Li, 2021); cap-and-trade regulations compel financially constraints companies to relocate production outside policy affected area (Bartram et al., 2022); Environmental enforcement actions (EPA) enforced firms hire more green inventors and increase their green innovation outputs significantly (He and Qiu, 2025).

Furthermore, companies adjust their corporate governance and operating strategies accordingly to hedge climate risks. Firms increase cash holdings and reduce leverage to strengthen their capacity to withstand climate hazards (Huang et al., 2018; Ginglinger et al., 2023); companies involve in more CSR activities as they are in high climate risks countries (Ozkan et al., 2023); firms in climate vulnerable regions produce more green innovation to adopt climate risks (Liu et al., 2024); customers tend to end partnerships with suppliers affected by heat waves and instead contract with vendors with a lower climate-related risks (Pankratz and Schiller, 2024). Aligned with this, options are widely used to hedge climate risks. Sustainability-linked bonds incorporate embedded ESG options, with pricing connected to penalty magnitudes, effectively hedging ESG-related risks (Feldhutter et al., 2024).

Although investors are aware of the climate risks, the perceived risks are not the same as the actual risks. In other words, the risks have not fully priced and explored. For example Pankratz et al. (2023) illustrate that heat, as a major climate risk, has not been fully priced in capital market, as firms expose to extreme temperatures fall short of analyst forecasts and suffer negative abnormal returns at earnings announcements, implying that markets underestimate heat as a climate risk; Hong et al. (2019) examine the impact of drought severity on food stock returns, and they document a lack of attention of climate risks and stock market underreact to this climate information, reflecting in inefficient pricing of drought risk; Kruttli et al. (2025) assess stock-option pricing around hurricanes and show that, despite sustained post-landfall uncertainty, implied volatility spikes only briefly, indicating that markets systematically underprice climate-related risk. However, the perceived risks are not constant all the time, people update their beliefs especially after direct exposing to natural disasters, and perceived risks to climate change increase rapidly.

5.2.2 Updating Beliefs and Economic Impact

People update their beliefs about climate risks and make economic decisions. Zaval et al. (2014) state that people who directly encounter unusually warm conditions tend to perceive higher climate-related risks in US. Specifically, Choi et al. (2020) observe that people raise attentions to global warming after experience abnormal higher temperature, and they revise their beliefs about climate risks. Ilhan et al. (2021) report that the cost of option for downside tail-risk protection is disproportionately greater for firms with higher carbon intensity and the costs surge further during periods of heightened public concern over climate change. The updated belief directly increases both the willingness to engage in mitigation actions and the endorsement of related policy measures (Andre et al. 2024), such as retail investors selling carbon-intensive firm in warm weather (Choi et al., 2020); fund managers supporting corporate environmental policies after experiencing with high temperatures or pollution (Di Giuli et al., 2024; Foroughi, et al., 2024); institutional investors vote to support environmental proposals (Fich and Xu, 2025). Therefore, I are intrigued to investigate whether climate risks have effect on cross-border VC investors decisions.

In addition, environmental issues induce anomality and behavioural bias in investments. Kamstra et al. (2000) find that daylight saving time disrupts traders sleep patterns, and negatively influence stock returns. Furthermore, a number of research have identified a consistent "weather effect" linking local weather conditions to stock market returns. For instance, Saunders (1993) discovers that increased cloud cover over New York City is significantly associated with lower NYSE index returns; Kamstra et al. (2003) record the seasonal affective disorder (SAD) effect on stock returns, which examines a profound negative effect of daylight length on people's moods, risk tolerance, and stock returns; Hirshleifer and Shumway (2003) using international data and demonstrate that sunny days boost trader mood, and in turn drives positive stock returns. Moreover, weather-based moods affect investors' perceptions about market mispricing and trading behaviours. Goetzmann et al. (2015) provide evidence that institutional investors perceive higher overpricing for individual stocks and Dow Jones Industrial Index in cloudy days and they are more are inclined to sell equities. Cloud-induced mood effects extend beyond public markets: under heavier cloud cover, investors contribute less to equity crowdfunding campaigns (Shafi and Mohammadi, 2020).

Besides cloud cover, scholars find that air pollutions significantly influence financial market. It dampens subsequent earnings forecasts (Dong et al., 2021), induces excessive trading activities (Huang et al., 2020), and leads to cognitive bias and increases investors' disposition effects (Li et al., 2021). In addition, extreme heat also alters market dynamics. Trading volumes decline significantly on hot days (Peillex et al., 2021), and earnings across more than 40% of industries are considerably negatively affected (Addoum et al., 2023). This study extends this strand of literature on how climate related factors effect investor belief and investing behaviours, particularly cross-border VC investors.

5.2.3 VC Investors Manage Climate Risks

However, not all ESG holdings and social-conscious investments are equally influential, and realization of climate risk not correlated with economic conditions (Stroebel and Wergler, 2021; Giglio et al., 2025). Heeb et al. (2023) state that while investing in sustainable investment, investors do not pay significantly more for more impact. Consistent with this, Berk and Van Vinsbergen (2025) find the socially conscious investors make limited impact on cost of capital and hardly affect real investment decisions. However, investors through funds are more powerful and influential than they are in public companies to the development of portfolio companies. Considering VC's key role in economic growth and entrepreneur company developing, I are particularly interested in how cross-border VCs evaluate and manage climate risks.

There is a growing discussion about whether private investors impede companies sustainable growth through withholding information and problematic carbon emissions companies transfer to private market. Duchin et al. (2025) record that companies under significant environmental scrutiny sell their polluting plants to purchasers who are often private, non-ESG-rated firms. However, Shive and Forster (2020) show evidence that no differences in pollution levels between PE-backed firms and public firms. Furthermore, Abraham et al. (2024) find that PE firms increasing demand for ESG information actively drive ESG performance. However, how VC investors manage climate risk and support sustainable development is still a nascent topic.

Pastor et al. (2021) document that although sustainable investing earns a lower return, green assets serve as an effective tool to hedge climate risks and generate excess returns when ESG factors experience favourable shocks, such as consumers demand for green goods, and investor preference for green holdings. Furthermore, entrepreneurship is seen as the driving force of sustainable development, which anticipate that innovative entrepreneurship to bring next industrial revolution and a sustainable future (Pacheco et al., 2010). Therefore, sustainable entrepreneurship (SE), defined as entrepreneurs set goals beyond purely financial profits and embrace broader ESG objectives, has attracted considerable interest by scholars recently. Cohen and Winn (2007) and Patzelt and Shepherd (2011) identify the opportunities for ventures by incorporating pro socio-environmental values into their core business activities; Schaltegger and Wagner (2011) find the factors that enable startups to pursue sustainable innovation and social entrepreneurship simultaneously; Cohen (2006) research about elements shape a sustainable entrepreneurship ecosystems, such as formal and informal networks, built infrastructure, and local culture, and illustrates how each fosters sustainable venture creation. Moreover, Mansouri and Momtaz (2022) extend the study in valuation in the context of Initial Coin Offering (ICO) and demonstrate that startups with strong ESG orientation attract more investor interests and receive substantially higher valuations. However, investing in sustainability is different from typical investments. Cumming et al. (2016) identify that cleantech VC requires more capital, are riskier, less likely to scale up, and more difficult to exit. Then, Petkova et al. (2014) find that reputable VCs are more likely to invest in the emerging clean energy sectors, and they also employ risk reduction strategies more extensively.

Besides reputable VCs, there is a group of VC investors, distinct from traditional VCs, and they are driven by both financial and social returns, called impact investors. Impact investors' top three selection criteria are the authenticity of the founding team, the importance of the societal problem targeted by the venture, and the venture's financial sustainability (Block et al. (2021). As for the financial returns, although impact funds underperform than traditional VC funds, investors are willing to accept a lower IRR ex ante for impact funds (Barber et al., 2021). Despite lower financial performance, impact funds create social benefits for disadvantaged areas and minorities people. Cole et al. (2023) report that compare to traditional VCs, impact investors are more patient and risk tolerant, and they are more likely to invest in poorer, disadvantaged regions in US and the world; then in post-investing stage, Lerner et al. (2025) show that impact investors consistently hire and support minorities and unskilled workers to achieve social goals beyond pecuniary goals. Jeffers et al. (2024) explain that impact funds could be an effective instrument to hedge climate risks, due to a lower exposure to market risk, compared to other private market investments.

Furthermore, Huang et al. (2024) examine how US VC investors navigate natural disaster in domestic investments. They discover that operational disruptions and increased information asymmetry caused by natural disasters drive venture capitalists toward more cautious investment approaches. VC investors significantly reduce their investments in disaster zone, and the disasters negatively influence VC exits, exhibiting a declining likelihood of successful exits and extending time going public. Beyond domestic market, I assess how climate risks impact cross-border investment outcomes, expanding the investment scope and incorporate country characters in climate related information processing.

5.2.4 Hypothesis Development

This study is inspired by Alok et al. (2020), which assess mutual fund managers reactions on natural disasters by analysing natural disaster data and mutual fund data in US. They exhibit that managers in disaster-affected regions are more likely to invest in other area stocks than managers located in unaffected regions due to salience bias. Building on this study, I use global country level climate risks data with VC investment data to examine whether climate risks induce any irrational bias in cross-border VC investors investments selections and whether climate risks, as a result, influence investments performance.

H1: Cross-border Investments

I draw on insight from finance and psychology to hypothesize that experiential learning and salience bias drive cross-border VC investors deal selections decisions. Perceived risks, shaped by personal experience and accessible information, guide decision making. According to experiential learning theory, after individuals immerse in experiences, they reflect on and analyse these encounters to develop abstract concepts, and ultimately apply these insights in new situations (Boud et al., 1985; Kolb, 1984; Choi et al., 2020). Andre et al. (2024) illustrate that informing U.S. adults of the true extent of climate-friendly behaviours significantly increases their readiness to combat climate change and their supports for related policies, particularly among those most doubtful about global warming's reality and risks. Consistent with this, Choi et al. (2020) show that unusually high temperatures heighten public concern for global warming, shown as increased search volume in Google about global warming in warm days, and prompt retail investors to divest from carbon-intensive stocks, which subsequently underperform low-emission firms despite no change in fundamentals. In addition, following Morningstar's introduction of its carbon risk metrics in April 2018, funds designated as "low carbon" experienced a substantial surge in capital inflows, and mutual fund managers swiftly curtailed allocations to high carbon risk companies (Ceccarelli, et al., 2024). Institutional investors vote to support pro-environment proposals after affected by hurricanes (Fich and Xu, 2025). Building on experiential learning theory, I posit that VCs investors from high climate risks countries experience and acknowledge the loss of climate risks. They endure direct losses and recovery challenges, heightening their sensitivity to such threats. Consequently, they actively pursue opportunities in other countries with low climate exposure. Thus, I hypothesis that VC investors from high climate risk countries exhibit a greater propensity to invest abroad to mitigate climate risks.

In addition, previous studies show that salience bias shapes how people process environmental information. Salience bias is a theory explaining choices are misleading based on context. This bias occurs when individuals assign disproportionate weight to salient outcomes that are most cognitively accessible, typically due to vividness, temporal proximity, or emotional intensity, and thus overestimate the likelihood (Tversky and Kahneman, 1973). Bordalo et al. (2012) develop a model of decision-making under salient risks, explaining that when a rare downside event is prominent and salient, individuals tend to exaggerate its likelihood and behave more conservatively toward assets vulnerable to that event. Then Bordalo et al. (2013) show that consumers disproportionately gravitate toward salient attributes, shown as people prefer offerings with the highest perceived quality-to-price ratios. In financial market, Bernile et al. (2021) notice that after natural disasters, fund managers become more risk averse and tend to adopt a more conservative strategies, significantly decreasing their fund's volatility. Dessaint and Matray (2017) discover that managers affect by hurricane increase their cash holdings afterwards and also express their concerns about hurricane risks in financial files. Alok et al. (2020) indicate that upon direct expose to a natural disaster, fund managers feel the disaster impact immediately and then they divest from affected-region equities. This firsthand encounter intensifies the salience of disaster risks, prompting an immediate portfolio reallocation of disaster zone stocks. Therefore, individuals who experience natural disasters and climate shocks exhibit heightened awareness of climate risks, potentially triggering salience bias. Accordingly, I hypothesize that VC investors based in high climate risk countries are more inclined to pursue cross-border investments.

H1: VC investors from high climate risk country are more likely to make cross-border investments.

H2: Physical Risk

Beyond influencing cross-border VC investments selections, climate change risks also exert a profound effect on investment performance. Academics distinguish these climate-related risks into two main categories, physical risks, and transition risks. Accordingly, the second part of thestudy assess how each risk type affects the performance of cross-border VC investments.

Physical risks quantify the damages resulting from climate-related events, especially natural disasters, on firms operating, financing, and corporate governance. Natural disasters here include meteoritical phenomena, such as heatwaves, floods, droughts, and hurricanes, as well as geophysical events, like earthquakes. In addition to damaging ecosystems and infrastructure, these catastrophes also cause severe economic and human losses from three aspects. First of all, affected by natural disasters, corporates experience directly operation disrupt and reduced profitability. Rising temperatures undermine labour efficiency (Zhang et al., 2018), increased rainfall volatility induces extra employment costs (Downy et al., 2023), coastal real estate loses value with sea-level rise (Bernstein et al., 2019), drought intensity negatively affects firm profitability (Hong et al., 2019), and heat exposure decreases firms' revenues and operating incomes (Pankratz et al., 2023). Secondly, increased physical risks are seen as increased uncertainty and corporates adapt their financing and governance to mitigate the risks. Ginglinger, and Moreau (2023) show that companies confronting elevated physical climate risk incur greater expected distress and operating costs, prompting them to reduce leverage. Managers increase cash holdings following hurricane exposure (Dessaint and Matray, 2017), and rising temperatures (Gounopoulos and Zhang, 2024); companies are more likely to end relationships with suppliers located in high physical risk regions (Pankratz and Schiller, 2024). Thirdly, on the other hand, the uncertainty spread into capital market and investors value the risks significantly, as increased costs of capital. Huang et al. (2022) state that the greater physical climate risks, through the disruptions to supply chain, operations, and markets, heighten a firm's credit risks for its lending banks, resulting in more stringent financing terms of loan contracts. In addition, Huang et al. (2024) indicate that VCs limit funding in areas prone to frequent or severe natural disasters and that such exposure is associated with a worse financial performance, as lower exit probabilities and longer IPO timelines. Therefore, I infer that physical risks negatively impact cross-border VC investment success.

H2: cross-border VC investments in countries with high physical risks are less likely to have success exits.

H3: Transition Risk

Besides physical risks, Bolton and Kacperczyk (2023) highlight transition risks of climate risks, which are the uncertainties when transitioning from a fossil fuel-based to a low-carbon economy, involving policy shift, reputational effects, changing consumer preferences, evolving social norms, and technological innovation.

For example, various policy instruments, such as carbon taxes, cap-and-trade, subsidies, and emission trading, steer companies toward lower carbon output. Sweden's carbon taxes significantly reduce CO2 emissions from its manufacturing sector (Martinsson et al., 2024), while higher emissions taxes compelled manufacturers to boost R&D in clean technologies and adopt sustainable processes (Brown et al., 2022). In addition, Dasgupta et al. (2023) and He and Qiu (2025) document reduced toxic discharges and accelerated green innovation following EPA (Environmental Protection Agency) enforcement. In general, Ciccarelli and Marotta (2025) state that countries are less vulnerable to climate risks when they have adopted a carbon tax and other adapting plans.

Moreover, consumer preferences shifting, and social norms evolving heighten uncertainty around the transition toward a low-carbon economy. Fund investors are demanding for ESG disclosures (Abraham et al., 2024); investors with pronounced prosocial commitments divest from pollutive assets and transfer them to investors with weaker prosocial preferences (Duchin et al., 2025); and investors express a willingness to accept lower yields on bond with ESG options (Feldhutter et al., 2024). Moreover, technological innovation increase companies' resilience to adapt to climate changes and mitigate transition risks (Gerarden, 2023; Sautner et al., 2023a). These factors facilitate the transition to carbon neutrality but simultaneously introduce uncertainties for companies and reduce the financial performance. Accordingly, I investigate the economic implications of these transition risks, especially policy shocks.

A number of studies demonstrate that environmental policy stringency and uncertainty materially affect financial performance of assets. Ilhan et al. (2021) indicate that volatility in climate regulations is reflected in option prices, with contracts on high-emission firms trading at a premium to hedge against downside risks related to climate policy uncertainty. Moreover, investors ask for higher returns for such firms as compensation for a higher exposure to regulation regime change risk (Hsu et al. 2023). Consistent with this, investors demand greater returns in jurisdictions with more stringent climate policies (Bolton and Kacperczyk 2023; Zhang 2024). Such policy shocks also induce capital structure adjustments: carbon-intensive companies reduce leverage in response to heightened policy uncertainty (Nguyen and Phan 2020). Therefore, building on previous studies, I expect that transition risks negatively impact cross-border VC investment success, while higher adaptation readiness reduces transition risks. Therefore, I hypothesis:

H3: cross-border investments in countries with stronger adaptation readiness are more likely to have success exits.

5.3. Data and Sample Selection

In this part, I explain the databases used in this study and the process of sample selection.

5.3.1 Database

The data is compiled from three parts, VC investments, climate risks, and country data. The VC investments data is collected from Refinitiv Eikon, providing comprehensive details on VC investors, funds, and portfolio companies. It includes investment dates, investments size, specific characteristics of portfolio companies, such as age, location, industry, as well as VC exit events, such as IPOs, trade sales, write-offs, and exits dates. Following Khurshed et al. (2020), indicating that the globalization of the VC industry began in the mid-1990s, I start the sample period in 1996.

The climate risk data is sourced from Climate Risk Index (CRI), has been published by Germanwatch, since 2006, and Norte-Dame Global Adaptation Initiative (ND-GAIN). The global Climate Risk Index has been extensively used in climate risk studies by Huang et al. (2018), Bolton and Kacperczyk (2023), and Ozkan et al. (2023). The index quantifies weather-related economic losses by country, assessing annual impacts of extreme weather events such as storms, floods, and temperature extremes. The index incorporates four key indicators: the total number of deaths, deaths per 100,000 inhabitants, economic losses in USD (adjusted for purchasing power parity), and losses relative to gross domestic product (GDP). To enable meaningful cross-country comparisons regardless of population size or economic scale, the index includes CRI scores and relative rankings rather than absolute values.

Annual CRI scores reflect data from two years prior to the publication year; for instance, the 2012 score is based on events occurring in 2010. Additionally, the index includes a long-term climate risk score, which aggregates data over the preceding 20 years, providing a cumulative measure of climate vulnerability. This study follows Huang et al. (2018) and Bolton and Kacperczyk (2023) in utilizing the annual CRI scores. The latest available version is Global

Climate Risk Index 2021 (Eckstein et al., 2021), which reports weather related long-term loss events from 2000-2019, and annual country CRI score in 2019. Therefore, I use the available annual CRI scores for 202 countries from 2004 to 2019 in the main analyses.

Moreover, I employ the Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index from the University of Notre Dame as an alternative climate risk proxy. ND-GAIN provides publicly accessible data on countries' vulnerability to climate-related disruptions and evaluates their capacity to leverage public and private investments for adaptation. This index is commonly utilized in climate risk research (e.g., Ozkan et al., 2023; Pankratz and Schiller, 2024). In this study, I focus specifically on the climate vulnerability and adaptation readiness.

The climate vulnerability index is a proxy of a country's sensitivity to the adverse effects of climate change, and it is calculated from six sectors of food, water, health, ecosystem services, human habitat, and infrastructure. Each sector is in turn represented by six indicators that represent three cross-cutting components: the exposure, sensitivity, and adaptive capacity of the sector to climate-related or climate-exacerbated hazards. Therefore, the vulnerability is composed of 36 indicators. However, different from CRI, vulnerability is not an event-based measure.

Additionally, the readiness index evaluates a country's capacity to leverage investments into effective climate adaptation actions. ND-GAIN quantifies this capacity by calculating a weighted average of three subcomponents: economic, governance, and social readiness. Economic readiness reflects the investment climate that enables private sector capital mobilization. Governance readiness assesses societal stability and institutional quality, measured through political stability, control of corruption, rule of law, and regulatory quality. Social readiness captures social conditions that promote efficient and equitable use of investments, including social inequality, ICT infrastructure, education, and innovation. Together, these nine indicators comprise the overall climate readiness score.

Furthermore, I use natural disaster events data from EM-DAT by centre for Research on Epidemiology of Disasters (CRED 2011) at the University of Louvain (Belgium) in robustness test. The EM-DAT is an open access database, and documents over 26,000 significant disasters globally from 1900 to the present. It aggregates information from diverse sources, including United Nations agencies, NGOs, reinsurance firms, research institutions, and media outlets.

EM-DAT is widely used in cross-country economic research on natural disasters (e.g., Strömberg 2007; Noy 2009; Pankratz and Schiller, 2024).

In addition, I obtained country-level macroeconomic indicators from World Bank's World Development Indicators (WDI) Database. Specifically, I compiled annual data on GDP, population size, number of domestic listed companies, and stock market capitalization for each country throughout the study period.

5.3.2 Sample Selection

The sample selection begins with all venture capital (VC) investments recorded in Eikon from 1996 onwards. I restrict the sample to companies that have exclusively received funding from VC investors. Further, as highlighted by Li et al. (2014), the initial funding round is pivotal for VC investors, reflecting critical selection, evaluation, and strategic decision-making processes. So, I focus on firms that have received investments starting from their initial funding round, allowing us to examine the impact of this first investment. In addition, this approach also helps mitigate alternative factors related to VC exits, addressing concerns of potential reverse causality. Furthermore, I exclude "other" and "real estate" stage, and missing nation VCs and PCs.

Subsequently, I identify cross-border VC deals, defined by different headquarters nations between the VC firms and portfolio companies. The final sample includes 240,651 deals, where cross-border VC investments account for 24.39%, while 75.61% are domestic VC investments. Utilizing detailed information on VC firms and portfolio companies, I construct the main sample employed in the analysis.

5.4. Variable Definition and Construction

In this session, I present the main variables I used in the tests, and their constructions.

5.4.1 Dependent Variables

Firstly, I assess the likelihood of VC investors making cross-border investments after experiencing high climate risks. I use a binary dummy variable, *CBVC,* to capture whether the investment is domestic or cross-border investment. CBVC equals to one indicating a cross-border investment and zero otherwise (Dai et al., 2012; Buchner et al., 2018).

A primary objective of VC investments is to generate financial by successfully converting investments into cash. Therefore, secondly, I investigate whether climate risks of portfolio company affect exit outcomes. Previous VC literatures suggest that two profitable exits, initial public offering (IPOs) and acquisitions, are commonly used to define successful exits. IPOs are the primary exits strategy for VC-backed companies, as they yield superior returns for VCs and allow entrepreneurs to retain greater control post-listing compared to acquisitions (Cumming, 2008). Secondary to IPOs, trade sales to larger firms or acquisitions offer another profitable exit route, particularly under adverse macroeconomic, illiquid, or undeveloped capital markets (Cumming et al., 2005; Nahata et al., 2014).

Therefore, in this study, the successful exits are evaluated at the deal level as the portfolio companies exit via IPOs or M&As. I track the exit outcomes until June 2025 to observe their success exits, thus allowing for a minimum three-year window to achieve an exit for an investment made in late 2021 (Khurshed et al., 2020). I use a binary dummy variable, *Success*, that equals one for successful exits, and zero otherwise.

5.4.2 Independent Variables

I utilize Global Climate Risk Index (CRI) developed by Germanwatch, which quantifies country-level climate risks based on the frequency of climate-related damages, as an independent variable. Specifically, CRI proxies a country's exposure and vulnerability to extreme weather events, such as storms, floods, and heatwaves, capturing direct consequences including fatalities and economic losses (Kreft and Eckstein, 2014). The index incorporates absolute value of total deaths, deaths per 100,000 inhabitants, economic losses in USD adjusted for purchasing power parity (PPP), and losses relative to GDP. A country's CRI score is computed as the average rank across these four indicators, with higher scores indicating greater climate risk (Bolton and Kacperczyk, 2023). In addition, I use annual CRI rank in the robustness tests. CRI index has been commonly utilized in examining the economic impact of country climate risks on firm performance, corporate social responsibility, and financing decisions (Huang et al., 2018; Ozkan et al., 2023).

Furthermore, following Ozkan et al. (2023), to validate the robustness of the examination, I adapt the measurements (*Vulnerability* and *Readiness*) from the ND-GAIN as alternative indicators of climate risk as independent variables. Similar to CRI, the *Vulnerability* index evaluates the physical risk of climate risks, which is a country's sensitivity to the adverse effects of climate change. However, *Vulnerability* is not measured from specific extreme climate events. Instead, *Vulnerability* is assessed by evaluating a country's overall risk, considering its exposure, sensitivity, and adaptive capacity across sectors such as food, water, ecosystem service, human habitat, and infrastructure. A higher *Vulnerability* suggests a greater climate physical risk.

In addition, I use *Readiness* index to measure a country's transition risk of climate risk, following Pankratz and Schiller (2024). This index assesses the adaptation capacity to climate changes. Specifically, I employ overall *Readiness*, which is a weighted average of economic, governance, and social readiness for climate change adaption. I examine the impact of overall readiness as well as each factor on successful exits in later tests. *Readiness* is measured on a 0 to 1 scale, with higher values reflecting greater adaptive capacity to climate change.

5.4.3 Control Variables

The estimations account for characteristics of VC investors, deals, and countries that affect cross-border VC investment decisions and exit outcomes. I follow the control variables used in Buchner et al. (2018), including VC age, fund age, the number of VC investors and deal size. VC age is the difference between VC investment year and the VC investor founded year, as an indicator of VC experience. Giot and Schwienbacher (2007) and Espenlaub et al. (2015) observe that VC age influences VC exit performance and older VCs accelerate liquidation. Additionally, Kandel et al. (2011) note that VC funds typically have a fixed lifespan of 10 years, requiring liquidation of investments upon maturity regardless of costs. Investments made by older funds exhibit higher exit rates compared to those from younger funds (Buchner et al., 2018). Accordingly, I control for fund age in the analysis, defined as the difference between the fund's founded year and investment year.

In addition, the number of investors and deal size play crucial roles in shaping VC investment decisions and outcomes. According to Hoenen et al. (2014) and Huang et al. (2024), larger syndicates increase the likelihood of investment by distributing risk among participants.

Moreover, Tian (2012) finds that firms backed by VC syndicates have higher probabilities of successful exits. Additionally, Dai and Nahata (2016) demonstrate that greater funding amounts enhance the chances of exit success. Hence, the models include both the number of VC investors and the investment amount as control variables.

As for the country macroeconomic factors, I control for portfolio company country stock market capitalization. As highlighted by Black and Gilson (1998), a well-developed stock market enhances liquidity and provides effective exit opportunities for VC investors and portfolio firms, improving exit outcomes. Consistent with this, Nahata et al. (2014) provide empirical evidence that advanced stock markets facilitate successful VC exits. Consequently, I control for stock market development in examining of VC investment selection and outcomes. I measure stock market development as the stock market capitalization/GDP, noted as *Equity_Investee* (Dai et al., 2012).

In addition, to account for unobserved heterogeneity of the portfolio companies across time, industry, and financing stage, I include *Industry, Financing Stage*, and *Investment Year* fixed effects. I control for company characteristics by including Industry classification based on Eikon's subgroup 1 categories. Following Li et al., (2014), I add fixed effects of financing stages (i.e. seed, early stage, expansion, or later stage) using dummy variables. Additionally, *Investment Year* fixed effects are included to account for time-related and unobserved portfolio company factors. Heteroskedasticity-robust standard errors are clustered at the investee company level.

5.5. Summary Statistics

Table 3.1 reports the summary statistics of the main sample consists of all VC investments during 1996-2021. Panel A presents the descriptive statistics of the dependent variables and main independent variables, which are climate risk indicators. The sample comprises 240,651 deals, of which 24.39% are cross-border VC investments and 75.61% are domestic VC investments, comparable with the sample used in Dai et al. (2012). In addition, Table 3.1 shows that on average, there are 24% of deals exit successfully in the sample, consistent with previous study on VC investments performance (Li et al., 2014).

[Table 3.1: Summary statistics]

For the climate risk variables, I employ *CRI Score* and *Vulnerability* to quantify the country-year climate physical risk and *Readiness* to access climate transition risks. Consistent with Bolton and Kacperczyk (2023), I find that the *CRI Score* averages 37.70 for investee company countries, and 39.22 for VC investor countries. However, *CRI Scores* are available only for 2005-2019, resulting in incomplete coverage for some observations. In contrast, *Vulnerability* index is available and spans the entire sample period. The average *Vulnerability* for both investee and VC investor countries is approximately 0.32, with the standard deviation of 0.04, closely matching the summary statistics reported by Ozkan et al. (2023). Moreover, the transition risk is measured based on economic, social, and governance readiness, with the means of 0.60, 0.58, and 0.71. Three factors are combined into a weighted average index, overall *Readiness*. According to the Table 3.1, the overall *Readiness* for investee countries is 0.63 on average with variation of 0.0982, aligning with Pankratz and Schiller (2024).

Panel B displays summary statistics of the control variables. On average, each deal involves three VC investors. Furthermore, to normalize the data and address skewness, I apply the natural logarithmic transformation to the control variables, VC age, Fund age, and Investment Size. The natural logarithm transformed VC age has a mean of 2.66, whereas fund age averages at 2.27. In addition, the mean value of VC investment, after transformed, is around 1.425 million dollars. The deal characteristics are consistent with the sample used in Buchner et al. (2018). Moreover, stock market capitalization averages 1.16 times of the country GDP.

Panel C presents t-test results of the climate risk indicators by domestic investments group and cross-border investments group. The table reveals that the means of climate risk indicators are significantly different for two groups. Climate physical risk, measured by *CRI Score* and *Vulnerability*, are significantly higher for cross-border VC investments, compared to domestic. Specifically, *CRI Score_Investor* and *Vulnerability_Investor* are higher for cross-border than domestic, suggesting that investors from high climate risk countries are more likely to invest abroad, consistent with Hypothesis 1. Furthermore, The transition risk, proxy by *economic, social, governance*, and overall *Readiness*. The results indicate that countries engaged in cross-border investments exhibit higher *economic, social, governance*, and overall *Readiness,* reflecting greater overall capacity to adapt to climate changes.

Panel D provides the correlation matrix of all variables. The correlations between *CBVC* of VC investor's *CRI and Vulnerability* are positive, suggesting that VC investors originating from countries with greater physical risk tend to engage more frequently in cross-border investments, supporting Hypothesis 1. In addition, *Success* is negatively correlated with *CRI and Vulnerability*, and positively correlated with *Readiness* and its components, aligned with the conjectures in Hypothesis 2, that physical risk negatively affect success exits, and Hypothesis 3, adaption ability is positively influence success exits. In addition, *Readiness* is highly correlated with its components, economic, social, and governance.

5.6. Empirical Tests and Methodology

This section examines the influence of climate risks on VC investment choices and outcomes. First, I employ the probit regression to assess the relationship between climate risks and the likelihood of the cross-border VC investment. Specifically, I investigate how the climate risk of VC investors country affect VC investor decisions, using *CRI Score* and *Vulnerability* to quantify VC country climate risks. Moreover, I use the probit model to examine the role of climate risks on investment exit outcomes. I use *CRI Score* and *Vulnerability* to measure physical risk, and *Readiness* for transition risk. Furthermore, I utilize stacked Difference in Differences to address potential endogeneity concerns for cross-border VC investment decisions. Then, I apply the instrumental variable in Heckman two stage regression and cox proportional hazard model to access the effect of climate risks on exits performance. In addition, I use alternative measurements, *CRI rank, lagged CRI score,* and *lagged Vulnerability* in robustness test to support the findings.

5.6.1 CBVC

In this section, I examine Hypothesis 1, which expects that higher climate risk of VC investors country increases the likelihood of VC investors making a cross-border investment. I follow Li et al. (2014) and evaluate the effect of climate risk on the likelihood of a cross-border VC investment ($\mathbf{CBVC}_{i,j} = \mathbf{1}$) with the following probit equation:

Equation 8: Probit model for cross-border VC investment decision

$$\mathbf{P}(\mathbf{CBVC}_{i,j} = \mathbf{1}|\boldsymbol{x}_i) = \mathbf{F}(\mathbf{z}) = \frac{\boldsymbol{exp}(\boldsymbol{z})}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{z})}$$

where i is the VC investor, and j is the investee company, and $\mathbf{P}(\mathbf{CBVC}_{i,j} = \mathbf{1}|\boldsymbol{x})$ denotes the probability of the investment (i, j) is cross-border, conditional on the explanatory variables $\boldsymbol{x}$. The vector $\boldsymbol{x_i}$ comprises the Climate Risk in Investor country, deal characteristics, and country level characteristics. In addition, $\mathbf{F}(\mathbf{z})$ represents the cumulative distribution function of the standard normal distribution, with $\mathbf{z}$ expressed as a linear function of the covariates, $\mathbf{z} = \boldsymbol{x_i}'\boldsymbol{\beta}$. The parameters are estimated with the maximum likelihood method. I cluster standard errors at the investee company level and report the results in Table 3.2.

Table 3.2 reports the estimation results from Equation 8, employing probit model to assess the impact of VC investor country climate risks on the likelihood of undertaking cross-border VC investment. I use *CRI Score* in Panel A, and *Vulnerability* in Panel B. Across all specifications, climate risk coefficients are positive and significant at the 1% level, providing strong support for Hypothesis 1 that VC investors from high climate risks countries exhibit a greater propensity for cross-border investments.

Panel A employs the *CRI Score* as the climate risk measure. In Column (1), regressing *CRI Score* on the *CBVC* dummy yields a positive and significant coefficient of 0.0145, indicating that higher climate risk is associated with a greater likelihood of cross-border investments. Adding stage, industry, and investment-year fixed effects in Column (2) slightly increases the coefficient, which remains positive and significant. Furthermore, Columns (3) and (4) include additional control variables, with Column (4) also incorporating fixed effects. Across specifications, the results consistently show that higher climate risk in the VC investor's country significantly increases the probability of cross-border investment, with the effect size strengthening when controlling for VC, deal and country characteristics and fixed effects. According to Alok et al. (2020), mutual funds managers exhibit salience bias after experience natural disasters and avoid investing in disaster affected regions. I discover similar pattern in VC investors, who origin from high climate risks countries, are more likely to invest cross-border.

For the control variables, the results show that cross-border investments are associated with fewer participating investors. VC age and fund age have significantly positive coefficients, indicating that older VCs and more mature funds are more inclined toward cross-border deals, consistent with the findings from Chemmanur et al. (2016). In line with Buchner et al. (2018), larger investment sizes are more likely to be allocated internationally. Furthermore, the positive and significant coefficient on *Equity_Investee* suggests that more developed stock markets attract more cross-border VC activity (Dai et al., 2012; Buchner et al., 2018).

Panel B uses the ND_GAIN Vulnerability index to capture country-level climate risk. In Column (1), the *Vulnerability* of the VC investor's country is positively and significantly associated with the probability of cross-border investment, consistent with Panel A. This relationship remains robust after adding fixed effects (Column 2), additional controls (Column 3), and the full set of controls and fixed effects (Column 4). Across all specifications, *Vulnerability* coefficients are positive and significant at the 1% level, indicating that VC investors from countries with greater climate risk are more likely to invest abroad, strongly supporting Hypothesis 1. In addition, control variable estimates align with the estimations in Panel A (for robustness, I employ DiD analysis and use alternative measures of climate risk in later tables).

[Table 3.2: CBVC selection]

5.6.2 Physical Risk

I next test Hypothesis 2, which posits that higher physical climate risk in investee countries adversely affects cross-border investment exits performance. Exit success exit is defined as the investee company either going public or being acquired, captured by a binary dummy variable *Success*, with the value of one for successful exits, and zero otherwise. I estimate the probability of successful exits on physical risks using a probit model. Given the liability of foreignness and additional challenges encountered by VC investors in cross-border deals, previous literatures document lower successful exit rates relative to domestic investments (Zaheer, 1995; Nahata et al., 2014). Therefore, to mitigate the impacts from extraneous factors affecting VC exits, I restrict the sample to cross-border VC investments in investment performance estimations. All models incorporate control variables, and fixed effects. Table 3.3 displays the results.

Using the *CRI Score* in Columns (1) and (3) and *Vulnerability* in Columns (2) and (4) as alternative measures of physical climate risk, I find consistent evidence across all specifications. The significantly negative coefficients indicate that greater climate risk in the investee country is associated with reduced likelihood of success exits, supporting Hypothesis 2 that negative impact of physical risk on investment exit outcomes. In Column (1), the estimated coefficient of CRI Score is negative and significant at 1% level. Furthermore, I disentangle the negative effect, replacing the continuous CRI Score with quartile dummies, where Q4 represents the highest physical risk group, and I observe consistent results, that all coefficients are negative and significant at 1% level. In addition, I use Vulnerability in Column (2) and its quartile dummies in Column (4). The coefficient is consistently negative and significant at 10% level in Column (2). When using *Vulnerability Quartiles* in Column (4), coefficients for Q2-Q3 are negative but insignificant, whereas Q4 remains negative and significant, indicating that countries in the highest physical risk category experience reduced likelihood of successful exits significantly. Consistent with the findings in Ginglinger, and Moreau (2023) and Huang et al. (2024), higher physical risks deteriorate financial performance. Therefore, the results support Hypothesis 2, which states that physical risk in investee countries negatively affect successful exits.

Moreover, I find positive and significant effect of *number of VCs* on *Success*, which implies that larger syndicates enhance success exit rates, align with Tian (2012). The coefficients for VC age and fund age are positive but not significant. In addition, in line with the findings from Nahata et al. (2014), I observe that larger investment size and more developed stock markets are beneficial for successful exits, shown as a higher probability of successful exits.

[Table 3.3: Physical risk]

5.6.3 Transition Risk

In this session, I investigate the influence of transition risk on cross-border investment exits performance for Hypothesis 3. I expect that transition risk is negative affect investment exit outcomes, and higher adaption readiness promote higher success exit rates. A probit model is employed to assess the relationship between readiness ability and successful exits. I use cross-border investments sample as the examination for Hypothesis 2. Same as previous tests, the dependent variable is the probability of success exits, and the main explanatory variable is transition risk, measured by *Readiness* from ND-GAIN. Higher *Readiness* reflects greater capacity to adapt to climate change, which reduces a country's transition risk, and in turn, increases the likelihood of successful exits. I expect a positive coefficient of *Readiness* on *Success*. Table 3.4 illustrates the estimations.

Column (1) displays the regression results of overall Readiness on successful exits, including the control variables and fixed effects. The coefficient of Readiness is positive and significant at 1% level, which strongly supports the Hypothesis 3, stronger adaption readiness positively affects successful exits. In addition, I test three components of Readiness index, which are economic, social, and governance in Column (2), Column (3), and Column (4) respectively. The coefficients for economic and social are positive and insignificant, while that for governance is positive and significant. Governance serves as a proxy for society stability and institutional quality, measured through indicators such as political stability, control of corruption, rule of law, and regulatory quality. The findings indicate that a stable socio-political environments and high-quality institutions promote the likelihood of successful exits in cross-border investments, aligning with Dai et al. (2012), who find that stronger legal systems improve exits outcomes. The coefficients for control variables are consistent with the results in Table 3.3. Overall, the results are consistent with the prediction, support Hypothesis 3, which speculates that higher adaption readiness increases the likelihood of successful exits.

[Table 3.4: transition risk]

5.7. Robustness Test

5.7.1 Stacked Difference-in-Differences (DiD) (H1)

Furthermore, I employ difference-in-differences strategy to establish an explicit connection between the salience bias and the empirical identification. The theoretical argument suggests that exposure to salient climate-risk events may heighten investors' perception of environmental risk and subsequently influence their cross-border investment decisions. The key empirical challenge is that observed cross-border investments may reflect either salience-driven behavioural responses or rational investment choices based on superior information, market opportunities, or strategic portfolio considerations. The difference-in-differences design helps address this concern by comparing changes in investment behaviour before and after climate-risk exposure between treated investors and an appropriate control group. This allows the analysis to isolate whether investors exposed to salient climate-risk shocks become more likely to reallocate capital internationally, relative to investors not subject to the same exposure. In doing so, the empirical strategy directly tests the proposed salience-bias mechanism while reducing the likelihood that the results are driven by time-invariant investor characteristics or general trends in VC internationalisation.

Cengiz et al (2019) and Baker et al. (2022) suggest that stacked DiD identification constructs event-specific cohorts that containing treated units and "clean controls" units that remain unaffected during the event window, including not yet treated, later treated, and never treated. These cohorts are then stacked together, and then a two-way fixed effects regression is estimated on the stacked dataset with cohort-specific unit and time fixed effects.

Therefore, I implement a stacked difference-in-differences (DiD) strategy to mitigate the endogeneity problem. I examine the changes in the cross-border investments of VC portfolios surrounding salient climate disasters. Following Alok et al. (2020), I compare VCs exposed to a disaster (treatment group) with those yet to experience, scheduled to experience later, or never exposed to such events (control groups), based on their cross-border holdings.

I choose heatwave as the climate disaster event in DiD analysis, given that temperature is a key dimension of climate risk. Previous studies have used heat expose and abnormal temperature as a major climate event to study climate risks. Bansal et al. (2016) use temperature fluctuations to assess capital market responses to long-term climate risks. In addition, Pankratz and Schiller (2024) use the frequency of heat days to examine climate change effects on global supply chains. Therefore, I employ the annual count of heatwave events from EM-DAT, which defines a disaster when at least one of the following conditions is fulfilled: ten or more fatalities; at least one hundred individuals affected, injured, or displaced; a government declared state of emergency; or a request for international assistance.

The analysis proceeds in two stages. First, I construct cohort-specific datasets consisting of VC_PC pair investments from a heatwave-affected country (treatment group) and those from unaffected countries within a -3 and +3 years around the heatwave year ("clean controls"). This design avoids heterogeneous treatment bias by ensuring that previously treated VCs are never used as controls for subsequently treated ones. Second, I stack all the event-specific datasets in relative time, and conduct DiD analysis on stacked dataset, with the dependent variable being the cross-border investments portfolio weights of VC investors, calculated by the ratio of the dollar value of cross-border deals to the total dollar value of all investments by the same VC. Following Baker et al. (2022) and Fich and Xu (2025), I incorporate cohort-specific, VC_PC pair and year fixed effects through interactions with stack indicators. Table 3.5 reports the estimation results.

Panel A shows a positive and significant coefficient for Heatwave, indicating that, comparing with the control group, the treated VCs increase their cross-border investments by 1% following heatwave events, consistent with the finding of Alok et al (2020), after saliant natural disasters, fund managers located in disaster affected areas are propense to invest outsides of the areas, considering risks and salience bias. The results reinforce the baseline findings, and support Hypothesis 1.

The validity of the DiD approach relies on the assumption of parallel pre-disaster trends in the outcomes, which is cross-border investment portfolio weights, between treated and control VCs. While this assumption cannot be directly tested ex post, Panel B examines the outcome dynamics over the three years before and after a heatwave. By estimating coefficients for $Heatwave_{t+n}$, where n takes value from -3 to +3, I assess whether pre-treatment trends are parallel and address concerns that unobserved contemporaneous factors, rather than heatwaves, drive the estimated effects.

In Panel B, the coefficients for *Heatwave* are insignificant prior to the events, reflecting that VCs increase cross-border investments only after experiencing heatwaves. The effect is the strongest in the event year, with the coefficient of 0.0102, then becomes insignificant, aligning with Dessaint and Matray (2017) and Chang et al. (2018), who discover that attention to climate risks is temporary, and people overreact at the first place when events happen. However, after the event, the initial overreactions partially reversed as attention wanes. Nevertheless, I document the effect remains significant two years and three years post heatwaves, although with a reduced magnitude.

[Table 3.5: Stacked DiD]

5.7.2 IV & Heckman (H2)

Table 3.3 provides evidence that higher climate physical risk reduces the likelihood of successful exits. However, certain country- and firm-level characteristics are difficult to fully observe or control, raising the possibility of omitted variables that both elevate climate risk and impede exit outcomes, leading to potential endogeneity issue. To address these concerns, I adopt two strategies. First, I use instrument variable method to control for endogeneity in climate risk. Second, I employ the Heckman two-step model assess the relation between climate risk on exit outcomes.

For the instrument variable, I followed Huang et al. (2018) using country-year-level data of population density, obtained from World Bank. Population density is a plausible instrument for climate risk because it is positively related to climate risk, as more densely populated countries tend to face greater environmental pressure and higher exposure to climate-related disruptions. This provides a rationale for instrument relevance. Moreover, conditional on firm characteristics and macroeconomic controls, country-level population density is unlikely to directly affect the financial performance of a given firm (Huang et al., 2018). Instead, its influence is more plausibly transmitted through climate risk exposure, which makes it a reasonable instrumental variable.

Specifically, I employ OLS regression in the first stage to estimate climate risks according to the country population density with the dependent variable proxied by *Vulnerability*. In the second stage, I regress exit performance on the fitted values of climate risk from the first stage, incorporating the inverse Mills ratio to address selection bias, along with other control variables. Table 3.6 presents these estimation results.

Column (1) presents the first-stage results, suggesting that higher population density is associated with increased climate risk, consistent with expectations and Huang et al. (2018), that higher population lead to higher climate risks. Columns (2) and (3) report the second-stage estimates using the *Vulnerability* index and *Vulnerability Quartile*, respectively. While coefficients for Q2 and Q3 are insignificant, Q4, the highest risk group, has a negative and significant coefficient, indicating that countries with the greatest physical risks face a significant lower probability of successful exits. The result is robust to the previous findings and supports Hypothesis 2.

[Table 3.6: Heckman]

5.7.3 Cox hazard (H2)

I further test Hypothesis 2 by applying a Cox hazard model to examine the effect of climate-related physical risks on investment outcomes. The Cox model estimates the likelihood of exit conditional on survival, without assuming a specific distribution for exit times. In this model dependent variable is VC exit outcomes, is based on the natural logarithm of time to exit, which is measured from the date of first VC investment in the portfolio company. Exit duration is measured as the log of the days from the initial VC investment to exit, and it is censored for firms that unsuccessful exited as of June 2025. In this framework, a positive coefficient indicates a higher exit hazard and thus shorter expected duration, while a negative coefficient implies a lower successful exit rate and hence longer expected time to exit (Nahata et al., 2014). The results are reported in Table 3.7.

Column (1) presents the estimated coefficients, and Column (2) reports the hazard ratios. The coefficient for *Vulnerability* is negative and statistically significant in Column (1) and its hazard ratio is less than 1 in Column (2), indicating that higher *Vulnerability* reduces the probability of successful exits, and prolongs the time to exit. The findings are aligned with previous literatures about climate risks, indicating higher physical risk weaken financial performance (Pankratz et al., 2023) and lower investments returns Huang et al. (2024). The results are robust and consistent with Table 3.3, and support Hypothesis 2, which predicts that greater physical risk reduces the investment success exit rates.

[Table 3.7: Cox hazard]

5.7.4 Alternative Measurements

Besides *CRI Score*, I employ *CRI Rank* from Germanwatch as an alternative measure of country-level climate risk, where a higher rank indicates greater risk. CRI Rank is employed as a proxy in this robustness check to evaluate VC investment decisions in Panel A, and exits outcomes in Panel B. The results are reported in Table 3.8.

Panel A of Table 3.2 confirms robust results. Column (1) regresses investor-country CRI Rank on the cross-border investment dummy, Column (2) adds stage, industry, and year fixed effects, Column (3) includes control variables, and Column (4) incorporates both controls and fixed effects. Across all specifications, the coefficient on CRI Rank remains positive and significant at the 1% level, indicating that VC investors from higher-risk countries are more likely to engage in cross-border investments, similar results observe in the study about mutual fund managers investments selections (Alok et al., 2020) and domestic VCs investment choices (Huang et al. 2024). Furthermore, these findings, consistent with Table 3.2, support Hypothesis 1 and remain robust under this alternative measure of climate risk.

In addition, Panel B reports the probit estimates of *CRI Rank* on VC investment exit outcomes. Column (1) uses the continuous measure of *CRI Rank,* while Column (2) applies the *CRI Rank Quartile.* Across both specifications, the coefficients are negative and significant for all indicators, confirming robust results with Table 3.3 and supporting Hypothesis 2, that higher physical risk in investee company country reduces the likelihood of successful exits.

[Table 3.8: CRI ranking as alternative measure]

Moreover, I further employ lagged climate risk indicators to examine VC investment decisions in Table 3.9. The main explanatory variables in Column (1) to Column (4) are *lagged CRI Score*, and *lagged Vulnerability* in Column (5) to Column (8). The results are consistent with previous findings. The coefficients remain positive and significant through all models, confirming that higher climate risks in investor countries increase the likelihood cross-border investments. The results are robust and support Hypothesis 1.

[Table 3.9: lagged one as proxy]

5.8. Concluding Remark

This study examines the role of climate risk in shaping cross-border venture capital (VC) activity. Using global VC investments from 1996 to 2021, I show that investors from high-risk countries are more likely to invest abroad, consistent with salience bias. I further find that investee country climate risks significantly affect exit outcomes: greater physical risk lowers the probability of successful exits, whereas stronger adaptive capacity improves them. These results highlight the influence of climate risks in both motivating cross-border VC flows and shaping their ultimate success.

Moreover, I conduct a series of robustness tests to address potential endogeneity concerns. Implementing stacked DiD identification, with heatwaves as the climate disaster events to evaluate the cross-border investments weight change in VC investors' portfolios, I find that no significant portfolio adjustment until the heatwave happens. Investors increase cross-border investments after affected by heatwaves, consistent with the baseline findings. In addition, to mitigate omitted variable concerns in exit outcomes, I apply both instrumental variables and a Heckman two-stage model, obtaining results consistent with the baseline. A Cox hazard model further confirms the adverse effect of physical risks on exit performance. Finally, I use alternative measures and lagged indicators to examine the effect, and the results are robust and consistent. Alternative measures and lagged indicators yield similar conclusions. Collectively, these findings highlight the influence of climate risks on VC investment strategies and exit outcomes, underscoring their broader implications for entrepreneurial finance.

5.9. Appendix

Appendix A: Variable definitions

Dependent variables:

CBVC: A dummy variable equals to one if the investor and investee company are from different countries and zero otherwise. (Source: Eikon)

Success: A dummy variable equals to one if the investee company exits successfully through an IPO or M&A by June 2025 and zero otherwise. (Source: Eikon)

cb_weight: the cross-border investments portfolio weights of VC investors, calculated by the ratio of the dollar value of cross-border deals to the total dollar value of all investments by the same VC investor. (Source: Eikon)

Independent variables:

<u>climate risk variables:</u>

CRI_Score: Annual Climate Risk Score from Germanwatch Global Climate Risk Index report 2007-2021 (for Score 2005-2019). (Source: Germanwatch)

CRI_Rank: Annual Climate Risk Rank from Germanwatch Global Climate Risk Index report 2007-2021 (for Score 2005-2019). (Source: Germanwatch)

Vulnerability: Indexes evaluating a country's overall sensitivity to the adverse effects of climate change, considering its exposure, sensitivity, and adaptive capacity across sectors such as food, water, ecosystem service, human habitat, and infrastructure sectors. (Source: ND-GAIN)

CRI_Quartile: quartile dummies based on the CRI Score Index, where Q4 corresponds to the highest physical climate risk group. (Source: Germanwatch)

Vul_Quartile: quartile dummies based on the Vulnerability Index, where Q4 corresponds to the highest physical climate risk group. (Source: ND-GAIN)

Readiness: Indexes capturing the readiness for climate change adaptation at the country-level with respect to Economic, Social, and Governance aspects. Overall climate change adaptation readiness is a weighted average of the three aspects. (Source: ND-GAIN)
Heatwave: A dummy variable equals to one if the VC investor headquarter country is affected by heatwave (recorded as natural disaster in EM-DAT) within 12 months prior to investment date.

Control variables:

Country characteristics:
Equity_Investee: The natural logarithm of one plus the country stock market capitalization divided by the country GDP. (Sources: World Bank)
pop_density: The number of people living in per square kilometre of the land area. (Sources: World Bank)

VC and deal characteristics:
number_year_vc: The number of VC investors in the investment year. (Source: Eikon)
ln_vcage: The natural logarithm of one plus the age of the venture capital firm, measured as the difference between VC founded year and the investment year (Source: Eikon)
ln_fundage: The natural logarithm of one plus the age of the funds, measured by the difference between the fund's founding year and investment year (Source: Eikon)
ln_investmentsize: The natural logarithm of one plus the total amount invested by a VC firm in a given deal. (Source: Eikon)
Industry: A set of dummy variables for each company's industry. (Source: Eikon)
Year: A set of dummy variables for VC investment year. (Source: Eikon)
Stage: A set of dummy variables for the investee company financing stage, such as seed, early, expansion, and later stage. (Source: Eikon)

Appendix B: Tables

Table 3.1: Summary statistics

Panel A: dependent variables and climate risks variables

Variables	N	Mean	SD	p25	p50	p75	p90	Min	Max
cbvc	240,651	0.2439	0.4294	0.0000	0.0000	0.0000	1.0000	0.0000	1.0000
success	240,651	0.2414	0.4280	0.0000	0.0000	0.0000	1.0000	0.0000	1.0000
CRI Score_0_Investee	132,661	37.7044	23.5285	23.1700	30.0800	46.1700	71.0000	2.1700	126.1700
CRI Score_0_Investor	131,944	39.2217	24.6484	23.1700	30.5000	49.5000	73.8300	2.1700	126.1700
Vulnerability_investee	239,222	0.3196	0.0428	0.2971	0.3045	0.3286	0.3641	0.2528	0.6573
Vulnerability_investor	237,408	0.3172	0.0387	0.2971	0.3045	0.3240	0.3614	0.2528	0.5986
Readiness_investee	239,222	0.6323	0.0982	0.6085	0.6536	0.6887	0.7300	0.1480	0.8136
economic	239,219	0.6031	0.1374	0.5138	0.6096	0.6757	0.7971	0.0812	0.8806
social	239,222	0.5885	0.1017	0.5647	0.6204	0.6476	0.6602	0.0916	0.8020
governance	239,145	0.7055	0.1297	0.6998	0.7470	0.7876	0.8217	0.1581	0.8978

Panel B: controls variables

Variables	N	Mean	SD	p25	p50	p75	p90	Min	Max
number_year_vc	240,649	3.4338	2.3147	2.0000	3.0000	5.0000	6.0000	1.0000	28.0000
ln_vcage	237,959	2.6651	1.0708	1.9459	2.7081	3.6636	3.9703	0.0000	6.0845
ln_fundage	240,360	2.2728	1.2561	1.3863	2.1972	3.5264	3.9703	0.0000	5.3799
ln_investmentsize	240,651	1.4250	1.1492	0.4055	1.3350	2.2246	3.0000	0.0000	8.2376
Equity_Investee	196,713	1.1664	0.6158	0.7847	1.2453	1.4631	1.5851	0.0001	17.7723

Panel C: t-test

Variables	N(domestic)	Mean1	N(cbvc)	Mean2	MeanDiff	p-Value
CRI Score_0_Investee	102,013	35.514	30,648	44.994	-9.479	0.000***
CRI Score_0_Investor	102,010	35.515	29,934	51.853	-16.338	0.000***
Vulnerability_investee	181,552	0.317	57,670	0.329	-0.013	0.000***
Vulnerability_investor	181,513	0.316	55,895	0.319	-0.003	0.000***
Readiness_investee	181,552	0.640	57,670	0.609	0.031	0.000***
economic	181,552	0.610	57,667	0.580	0.030	0.000***
social	181,552	0.597	57,670	0.560	0.037	0.000***
governance	181,526	0.711	57,619	0.687	0.025	0.000***

Panel D: correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)criscore_Investee	1														
(2)criscore_Investor	0.6401	1													
(3)vul_Investee	0.0657	0.0716	1												
(4)vul_Investor	0.0607	0.1411	0.7043	1											
(5)readiness_Investee	-0.1236	-0.1236	-0.735	-0.5399	1										
(6)economic	-0.2362	-0.2027	-0.3864	-0.3114	0.8102	1									
(7)social	-0.0642	-0.0665	-0.727	-0.4775	0.787	0.3989	1								
(8)governance	0.0335	-0.0047	-0.7668	-0.5714	0.85	0.4515	0.6773	1							
(9)cbvc	0.1468	0.2993	0.1189	0.05	-0.1313	-0.1115	-0.1686	-0.0579	1						
(10)success	-0.1588	-0.1383	-0.1157	-0.1065	0.1694	0.1833	0.0662	0.1378	-0.0389	1					
(11)number_year_vc	-0.1358	-0.1174	-0.1353	-0.1103	0.128	0.0806	0.1285	0.1162	0.0034	0.1405	1				
(12)ln_vcage	-0.0109	0.0227	-0.0861	-0.084	0.0859	0.049	0.0716	0.0947	0.1497	0.0166	0.0298	1			
(13)ln_fundage	0.0037	0.0454	-0.0684	-0.0452	0.0495	0.023	0.042	0.0604	0.1678	-0.0224	0.0692	0.7945	1		
(14)ln_investmentsize	-0.1661	-0.1359	-0.0902	-0.0819	0.0805	0.0829	0.0717	0.0413	0.0449	0.1962	0.4006	0.0882	0.0523	1	
(15)Equity_Investee	-0.2335	-0.1647	-0.4183	-0.3086	0.4965	0.321	0.3915	0.5187	-0.0518	0.1207	0.1884	0.0672	0.0658	0.1692	1

Table 3.2: CBVC selection

This table reports probit regression estimating the probability of the cross-border investments. The dependent variables are *CBVC*, which is a dummy variable equals to one if the investor and investee company are from different countries and zero otherwise. The independent variables are *CRI Score* in Panel A, and *Vulnerability* in Panel B. Control variables are included in Column (3) and Column (4). Control variables are *number_year_vc, ln_vcage, ln_fundage, ln_investmentsize, and Equity_Investee*. Investee company financing *Stage*, investee company *Industry*, and Investment *Year* fixed effects are included in Column (2) and Column (4) in both Panels. Standard errors are clustered at the investee company level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: CRI Score as proxy for climate risk

	(1)	(2)	(3)	(4)
	cbvc	cbvc	cbvc	cbvc
CRI Score_Investor	0.0145***	0.0146***	0.0187***	0.0193***
	(0.0002)	(0.0003)	(0.0002)	(0.0003)
number_year_vc			-0.0057**	-0.0091**
			(0.0022)	(0.0043)
ln_vcage			0.0721***	0.0788***
			(0.0072)	(0.0100)
ln_fundage			0.1489***	0.1417***
			(0.0060)	(0.0084)
ln_investmentsize			0.1027***	0.0955***
			(0.0041)	(0.0063)
Equity_Investee			0.0545***	0.0685***
			(0.0069)	(0.0133)
_cons	-1.3567***	-1.6197***	-2.2940***	-2.3967***
	(0.0076)	(0.0844)	(0.0184)	(0.0950)
Stage		Yes		Yes
Industry		Yes		Yes
Year		Yes		Yes
N	131,944	131,944	131,944	131,944

Panel B: Vulnerability as proxy for climate risks

	(1)	(2)	(3)	(4)
	cbvc	cbvc	cbvc	cbvc
Vulnerability_investor	1.0871***	0.5062***	2.0138***	1.5287***
	(0.0709)	(0.1174)	(0.0877)	(0.1517)
number_year_vc			-0.0135***	-0.0217***
			(0.0017)	(0.0034)
ln_vcage			0.0755***	0.0841***
			(0.0053)	(0.0075)
ln_fundage			0.1525***	0.1411***
			(0.0044)	(0.0061)
ln_investmentsize			0.0431***	0.0349***
			(0.0032)	(0.0052)
Equity_Investee			-0.0200***	-0.0399**
			(0.0050)	(0.0174)
_cons	-1.0665***	-1.0275***	-2.0061***	-1.9379***
	(0.0227)	(0.0793)	(0.0318)	(0.0936)
Stage		Yes		Yes
Industry		Yes		Yes
Year		Yes		Yes
N	237,408	237,408	237,408	237,408

Table 3.3: Physical risk

This table reports probit regression estimating the probability of the cross-border investment successful exits. The dependent variables are *success*, which is a dummy variable equals to one if the investee company exits successfully through an IPO or M&A by June 2025 and zero otherwise. The independent variables are *CRI Score* in Column (1), *Vulnerability* in Column (2), *CRI Score_Quartile* in Column (3), and *Vulnerability_Quartile* in Column (4), respectively. Control variables and Investee company financing *Stage*, investee company *Industry*, and Investment *Year* fixed effects are included in all columns. Control variables are *number_year_vc, ln_vcage, ln_fundage, ln_investmentsize, and Equity_Investee*. Standard errors are clustered at the investee company level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	success	success	success	success
CRI Score_0_Investee	-0.0024***			
	(0.0008)			
Vulnerability_investee		-0.6237*		
		(0.3721)		
CRI_q1			.	
			.	
CRI_q2			-0.1389***	
			(0.0483)	
CRI_q3			-0.2141***	
			(0.0485)	
CRI_q4			-0.1529***	
			(0.0492)	
Vul_q1				.
				.
Vul_q2				0.0671
				(0.0490)
Vul_q3				-0.0298
				(0.0469)
Vul_q4				-0.1655***
				(0.0488)
number_year_vc	0.0602***	0.0472***	0.0597***	0.0446***
	(0.0093)	(0.0076)	(0.0093)	(0.0076)
ln_vcage	0.0074	0.0061	0.0144	0.0093
	(0.0217)	(0.0166)	(0.0217)	(0.0166)
ln_fundage	0.0004	-0.0097	-0.0020	-0.0150
	(0.0180)	(0.0136)	(0.0181)	(0.0137)
ln_investmentsize	0.1278***	0.1492***	0.1289***	0.1507***
	(0.0137)	(0.0116)	(0.0137)	(0.0117)
Equity_Investee	0.1375***	0.2026***	0.1263***	0.1633***
	(0.0312)	(0.0364)	(0.0314)	(0.0389)

_cons	-1.2029***	-1.0081***	-1.2053***	-1.1014***
	(0.2216)	(0.2308)	(0.2209)	(0.1899)
Stage	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	27,190	41,917	27,190	41,917

Table 3.4: Transition risk

This table reports probit regression estimating the probability of the cross-border investment successful exits. The dependent variables are *success*, which is a dummy variable equals to one if the investee company exits successfully through an IPO or M&A by June 2025 and zero otherwise. The independent variables are overall *Readiness* in Column (1), *Economic* in Column (2), *Social* in Column (3), and *Governance* in Column (4), respectively. Control variables and Investee company financing *Stage*, investee company *Industry*, and Investment *Year* fixed effects are included in all columns. Control variables are *number_year_vc, ln_vcage, ln_fundage, ln_investmentsize, and Equity_Investee*. Standard errors are clustered at the investee company level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	success	success	success	success
Readiness_investee	0.4979***			
	(0.1917)			
economic		0.2148		
		(0.1588)		
social			0.1259	
			(0.1432)	
governance				0.5364***
number_year_vc	0.0465***	0.0480***	0.0479***	0.0449***
	(0.0076)	(0.0075)	(0.0076)	(0.0076)
ln_vcage	0.0072	0.0071	0.0060	0.0085
	(0.0166)	(0.0166)	(0.0166)	(0.0166)
ln_fundage	-0.0107	-0.0093	-0.0084	-0.0115
	(0.0136)	(0.0136)	(0.0136)	(0.0136)
ln_investmentsize	0.1511***	0.1493***	0.1497***	0.1546***
	(0.0116)	(0.0116)	(0.0116)	(0.0117)
Equity_Investee	0.1679***	0.2046***	0.2138***	0.1452***
	(0.0395)	(0.0366)	(0.0353)	(0.0393)
Stage	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
_cons	-1.4543***	-1.3205***	-1.2844***	-1.5582***
	(0.2020)	(0.1928)	(0.1901)	(0.2014)
N	41,917	41,917	41,917	41,917

Table 3.5: Stacked DID

This table reports OLS regression assessing the cross-border investment weight change when heatwave happens. The dependent variables are *cb_weight*, which is the cross-border investments portfolio weights of VC investors, calculated by the ratio of the dollar value of cross-border deals to the total dollar value of all investments by the same VC investor. The independent variable is *Heatwave*, which is a dummy variable equals to one if the VC investor headquarter country is affected by heatwave. Panel A displays the regression results, and I include cohort-specific, VC_PC pair and year fixed effects through interactions with stack indicators in Panel A. Panel B presents the dynamic effects from 3 years before until 3 years after the heatwave. Control variables and Investee company financing *Stage*, investee company *Industry*, and Investment *Year* fixed effects are included in Panel B. Standard errors are clustered at the investee company level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: results

	(1)
	cb_weight
Heatwave	0.0105***
	(0.0037)
_cons	0.0577***
	(0.0001)
Year*cohort FE	Yes
VC_PC pair*cohort FE	Yes
N	947,473
R-sq	0.839
adj. R-sq	0.721

Panel B: parallel trend

	(1)
	cb_weight
$Heatwave_{t-3}$,	0.0045
	(0.0093)
$Heatwave_{t-2}$,	0.0032
	(0.0053)
$Heatwave_{t-1}$,	0.0058
	(0.0044)
$Heatwave_{t}$,	0.0102***
	(0.0034)
$Heatwave_{t+1}$,	0.0056
	(0.0036)
$Heatwave_{t+2}$,	0.0109***
	(0.0036)

$Heatwave_{t+3}$,	0.0057*
	(0.0032)
number_year_vc	0.0003
	(0.0003)
ln_vcage	-0.0026
	(0.0033)
ln_fundage	0.0016**
	(0.0008)
ln_investmentsize	0.0169***
	(0.0007)
Equity_Investee	-0.0138***
	(0.0048)
_cons	0.0247**
	(0.0105)
Stage	Yes
Industry	Yes
Year	Yes
N	73,887
R-sq	0.837
adj. R-sq	0.731

Table 3.6: Robustness: IV & Heckman

This table reports Heckman two stage results. Column (1) presents the first stage results, and Column (2) and Column (3) report the second stage results. The dependent variables are *Vulnerability* in Column (1) and *success* in Column (2) and Column (3). The independent variables are *pop_density* in Coulmn (1), *Vulnerability* in Column (2), and *Vulnerability Quartile* in Column (3), respectively. Control variables and Investee company financing *Stage*, investee company *Industry*, and Investment *Year* fixed effects are included in all columns. Control variables are *number_year_vc, ln_vcage, ln_fundage, ln_investmentsize, and Equity_Investee*. Standard errors are clustered at the investee company level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) first stage	(2)	(3)
	Vul_investee	success	success
pop_density	0.0000***		
	(0.0000)		
Vulnerability_investee		-0.3944	
		(0.4013)	
Vul_q1			.
			.
Vul_q2			0.0844
			(0.0588)
Vul_q3			-0.0213
			(0.0507)
Vul_q4			-0.1195**
			(0.0582)
number_year_vc	-0.0022***	0.0541***	0.0532***
	(0.0002)	(0.0099)	(0.0099)
ln_vcage	-0.0009*	0.0007	0.0030
	(0.0005)	(0.0183)	(0.0182)
ln_fundage	-0.0020***	-0.0132	-0.0142
	(0.0004)	(0.0150)	(0.0150)
ln_investmentsize	0.0015***	0.1593***	0.1613***
	(0.0004)	(0.0130)	(0.0130)
Equity_Investee	-0.0489***	0.1772***	0.1783***
	(0.0011)	(0.0643)	(0.0647)
lambda		2.8582	1.3800
		(2.2594)	(2.2912)
Stage	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
_cons	0.3892***	-2.7289**	-1.9257
	(0.0070)	(1.3552)	(1.3342)
R-sq	0.311		
adj. R-sq	0.310		
N	29,114	29,114	29,114

Table 3.7: Cox hazard

This table shows a Cox hazard model of VC exit rates estimated using maximum likelihood estimation. Column (1) reports the coefficients, and Column (2) shows the hazard ratio. Control variables and Investee company financing *Stage*, investee company *Industry*, and Investment *Year* fixed effects are included in both columns. Control variables are *number_year_vc, ln_vcage, ln_fundage, ln_investmentsize, and Equity_Investee*. Standard errors are clustered at the investee company level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	_t	_t (Hazard ratio)
Vulnerability_investee	-1.6555*	0.1910*
	(0.9233)	(0.1764)
number_year_vc	-34.6459	8.98e-16
	(1.5e+06)	(0.0000)
ln_vcage	-0.1471**	0.8632**
	(0.0639)	(0.05518)
ln_fundage	-0.0759	0.9269
	(0.0561)	(0.0520)
ln_investmentsize	0.1582***	1.1714***
	(0.0422)	(0.0494)
Equity_Investee	-0.3812***	0.6830***
	(0.1181)	(0.0807)
Stage	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
N	41,914	41,914

Table 3.8: CRI rank as proxy

This table reports probit regression using *CRI Rank* as an alternative measure for climate risk estimating the probability of the cross-border investment in Panel A, and the likelihood of successful exits in Panel B. The dependent variable is *CBVC* in Panel A, a dummy variable equals to one if the investor and investee company are from different countries and zero otherwise. The dependent variable is *success*, which is a dummy variable equals to one if the investee company exits successfully through an IPO or M&A by June 2025 and zero otherwise. The independent variable is *CRI Rank*. Control variables are included in Column (3) and Column (4). Control variables are *number_year_vc, ln_vcage, ln_fundage, ln_investmentsize, and Equity_Investee*. Investee company financing *Stage*, investee company *Industry*, and Investment *Year* fixed effects are included in Column (2) and Column (4) in both Panels. Standard errors are clustered at the investee company level and reported in parentheses

panel A: selection _investor

	(1)	(2)	(3)	(4)
	cbvc	cbvc	cbvc	cbvc
CRI Rrank_0_Investor	0.0105***	0.0105***	0.0139***	0.0141***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
number_year_vc			-0.0042*	-0.0098**
			(0.0022)	(0.0043)
ln_vcage			0.0624***	0.0755***
			(0.0072)	(0.0100)
ln_fundage			0.1610***	0.1450***
			(0.0060)	(0.00848)
ln_investmentsize			0.101***	0.0934***
			(0.0041)	(0.0062)
Equity_Investee			0.0580***	0.0625***
			(0.0069)	(0.0134)
_cons	-1.136***	-1.435***	-2.027***	-2.142***
	(0.0058)	(0.0838)	(0.0173)	(0.0936)
Stage		Yes		Yes
Industry		Yes		Yes
Year		Yes		Yes
N	131,944	131,944	131,944	131,944

Panel B: Success

	(1)	(2)
	success	
CRI Rank_0_Investee	-0.0016***	
	(0.0006)	
CRI Rank_q1		.
		.
CRI Rank_q2		-0.1264***
		(0.0468)
CRI Rank_q3		-0.2043***
		(0.0513)
CRI Rank_q4		-0.1416***
		(0.0491)
number_year_vc	0.0602***	0.0598***
	(0.0093)	(0.0093)
ln_vcage	0.0071	0.0139
	(0.0217)	(0.0217)
ln_fundage	0.0010	-0.0007
	(0.0180)	(0.0181)
ln_investmentsize	0.1281***	0.1284***
	(0.0137)	(0.0137)
Equity_Investee	0.1379***	0.1302***
	(0.0312)	(0.0316)
_cons	-1.2393***	-1.2131***
	(0.2201)	(0.2210)
Stage	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
N	27,190	27,190

Table 3.9: Lagged one as proxy

This table reports probit regression estimating the probability of the cross-border investments. The dependent variables are *CBVC*, which is a dummy variable equals to one if the investor and investee company are from different countries and zero otherwise. The independent variables are *lagged CRI Score* in Column (1) - Column (4), and *lagged Vulnerability* in Column (4) - Column (8). Control variables are included in Column (3), Column (4), Column (7), and Column (8). Control variables are *number_year_vc, ln_vcage, ln_fundage, ln_investmentsize, and Equity_Investee*. Investee company financing *Stage*, investee company *Industry*, and Investment *Year* fixed effects are included in Column (2), Column (4), Column (6) and Column (8). Standard errors are clustered at the investee company level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	cbvc	cbvc	cbvc	cbvc	cbvc	cbvc	cbvc	cbvc
CRI Score_l1_Investor	0.0146***	0.0146***	0.0186***	0.0191***				
	(0.0002)	(0.0003)	(0.0002)	(0.0003)				
Vul_l1_Investor					1.0491***	0.4884***	1.9680***	1.5058***
					(0.0702)	(0.1163)	(0.0868)	(0.1500)
number_year_vc			-0.0104***	-0.0122***			-0.0135***	-0.0217***
			(0.0023)	(0.0043)			(0.0017)	(0.0034)
ln_vcage			0.0812***	0.0876***			0.0755***	0.0841***
			(0.0075)	(0.0104)			(0.0053)	(0.0075)
ln_fundage			0.1304***	0.1265***			0.1525***	0.1410***
			(0.0063)	(0.0087)			(0.0044)	(0.0061)
ln_investmentsize			0.0969***	0.0896***			0.0430***	0.0349***
			(0.0042)	(0.0064)			(0.0032)	(0.0052)
Equity_Investee			0.0893***	0.0634***			-0.0200***	-0.0398**
			(0.0072)	(0.0134)			(0.0050)	(0.0174)
_cons	-1.3440***	-1.6158***	-2.2691***	-2.2716***	-1.0549***	-1.0217***	-1.9923***	-1.9304***
	(0.0078)	(0.0888)	(0.0189)	(0.0969)	(0.0225)	(0.0791)	(0.0316)	(0.0933)
Stage		Yes		Yes		Yes		Yes
Industry		Yes		Yes		Yes		Yes
Year		Yes		Yes		Yes		Yes
N	124,987	124,963	116,655	116,633	237,408	237,380	192,134	192,109

Chapter 6: Conclusion

This thesis empirically examines issues to advance our understanding of the role of cross-border VC investors. This thesis has presented three independent essays and addresses three issues about the role of cross-border VCs on innovation, how social connections affect cross-border VC investments, and how cross-border VCs incorporate climate risks in investments.

First, Chapter 3 of the thesis illustrates cross-border VC investors have a great impact on innovation than domestic VC, due to main three aspects. Cross-border VCs have less emotional attachments with local community, which induces less individual decision bias in investments and more commitment to investments. In addition, cross-border VCs can enhance innovation by effectively manage risks and greater tolerance for failure. Last but not the least, VCs from high innovation can diffuse knowledge to investee companies in lower-innovation countries, and therefore, increase their innovation. Thus, I hypothesis, and empirically observe a positive impact of cross-border VC investments on innovation.

Second, Chapter 4 of the thesis examines the role of social connections in cross-border VC investments selections, successful exits, and innovation outcomes. Since social connections can transmit information, alleviate information frictions, and build trust between counterparties, which could also further promote innovation, I hypothesis that cross-border VCs are more likely to invest in socially connected countries, and social connections enhance innovation. The results are consistent with the predictions. However, such social connectedness reduces the diversity of information, strengthens decision bias, I expect that social connectedness further undermines the success exits of cross-border VC investments and find the negative empirical relation between social connectedness and successful exits rates.

Third, Chapter 5 of the thesis assess the impact of climate risks in cross-border investments selection and exits. Given the impact of salience bias, I argue that VCs from high climate risks countries are more likely to make cross-border investments. They perceive high risks from climate change, and they seek investments opportunities outside to manage such risks. Furthermore, specifically, physical risks negative affect success exits, while higher adaptive ability, shown as lower transition risks, increase the likelihood of success exit rates. The empirical tests report the consistent results as the hypotheses.

The following sections are a summary of the main findings of this thesis, recommendations and implications for practices, limitations, and directions for future research.

6.1 Summary and Key Findings

Chapter 3 examines whether cross-border VCs have a greater impact on innovation than domestic VCs. Previous studies have investigated the significant role of domestic VCs in innovation, such as CVC and VC syndication foster innovation (Tian, 2012; Chemmanur et al., 2014). However, cross-border VCs are different from domestic VCs because of geographic distance, cultural and institutional challenges. There are extensive studies about cross-border VC investments, especially the liability of foreignness (Zaheer, 1995; Meyer and Shao 1995; Nahata et al., 2015; Buchner et al., 2018). However, the detailed relationship between cross-border VCs and innovation remains underexplored. This chapter aims to fill this gap and explores the uniqueness of cross-border VC and their influence on innovation.

Analysing VC investments since 1996 and tracking innovation outcomes through 2020, using a comprehensive international patent and VC database, empirically findings of this chapter show that there is no significant different impact of cross-border VC on innovation, comparing to domestic VCs. However, the results from subsample of companies with positive patent counts indicate that cross-border VC significant increase investee company innovation. Furthermore, considering most cross-border investments are made due to the saturated domestic market and the pursuit of new business opportunities (Buchner et al., 2018), I observe that most cross-border investments originate from high-innovation countries. Moreover, this raises concerns about potential selection bias, as cross-border VCs are more likely to invest in firms from low-innovation countries, and such selection bias induces downward bias in the estimations. Thus, I follow Tian (2012) to address this concern and employ Heckman two stage model with instrument variable to account for selection bias. After separating the selection of cross-border VCs, the results suggest that cross-border VCs have a positive and significant impact on the number of patents and citations, which means that cross-border VCs increase innovation outcomes significant and greater than domestic VCs. The results remain robust in subsample.

In addition, the empirically findings reveal that cross-border VCs employ distinct risk management strategies, demonstrating greater tolerance for failure and commitment to their investee companies. This results in longer investment durations, fostering innovation. The results also indicate that cross-border VCs contribute to innovation through knowledge diffusion. VCs from high-innovation countries transfer valuable knowledge to investee firms in low-innovation countries, spurring innovation. Robustness checks, including varying measurement windows and using alternative independent variables, confirm the reliability of our findings. Results hold even when using a 5-year window or replacing the cross-border VC dummy variable with the percentage of cross-border VCs. Further tests using Poisson and negative binomial regressions also support our conclusions.

Taken together, the findings of Chapter 3 contribute to the existing literature on the role of cross-border VC investors. Previous literature about cross-border VCs mostly focuses on the performance of cross-border VC investments (Nahata et al., 2015; Buchner, et al. 2018). However, due to the data limitation, the relationship between cross-border VC investments and innovation performance has not been extensively explored. This study employs a manually matched international patent and VC database to examine the impact of cross-border VC investors on innovation. In addition, this study contributes to the innovation literature by providing new evidence on cross-border investments, highlighting knowledge spillovers from high-innovation to lower-innovation countries, and revealing the distinct risk management strategies employed by cross-border VCs.

Chapter 4 studies the impact of social connections on cross-border VC investments selection and performance. Considering geographic distance induces extra costs and less involvement and monitoring to investee companies, VC investors are less likely to invest in distant companies and display a significant local bias in selections (Lerner, 1995; Cumming and Dai, 2010). However, as VC industry develops rapidly, VCs gain a diminished profits in domestic market, so VC investors start to seek opportunities beyond their local regions. Sorenson and Stuart (2001) underscore that social connections facilitate VC investors to expand the geographic scope of investments in the US VC industry. Furthermore, VC firms expand their investments globally, while how VC investors navigate challenges, such as the liability of foreignness, remains underexamined. Therefore, in the same vein, this study examines the role of social connectedness in cross-border VC investments, specifically in investment selections, success, and innovation performance.

This study applies the Social Connectedness Index (SCI), derived from aggregated Facebook friendship links, to quantify social connectedness between countries and merges it with a comprehensive dataset of venture-capital transactions and international patents, and examines deal formation, investment exits performance, and innovation outcomes of portfolio companies.

First, this study employs counterfactual analysis for the deal formation, by constructing a new sample of all potential VC-PC pairs from 2019, and the results show that cross-border VCs are more likely to invest in companies located in socially connected countries. Second, I examine the impact of such connectedness on success exits using logit and probit regressions. Both logit and probit regression results report that while social connectedness attracts investments as well as familiar bias, the success exit rates are significant negative related to social connectedness in cross-border VC investments, consistent with Gompers et al. (2016), that investors pay extra costs for their friendship. Third, I estimate the role of social connectedness on innovation, by utilizing the Poisson pseudo-maximum likelihood estimations, and find that social connectedness has a positive impact on innovation. I infer this is due to social connectedness promote knowledge spillover, facilitate communication, and breed trust.

Furthermore, this study establishes the causality between social connectedness and investment successful exits using Heckman two stage model with the instrument variable, the proportion of Internet users in VC countries, following Dai and Nahata (2016). This estimation mitigates the concern of omitted variables that influence the social connectedness and the investment performance simultaneously. Higher internet penetration tends to create a rich information environment and more social connections on Facebook, which transmit information and investment opportunities, and therefore, increase the propensity of cross-border VC investments. After incorporating the effect of internet penetrations and separating the propensity of cross-border investments, the estimations suggest that a greater social connectedness has a negative impact on successful exits. The results are consistent with the previous findings that social connectedness undermines the investment success.

These findings provide meaningful understanding of the impact of social connectedness on VC investments. Previous literature has explored primarily on the personally social connections (Sorenson and Stuart, 2001; Gompers et al., 2016), instead of general regional connectedness, due to lack of comprehensive data. Moreover, Bottazzi et al. (2016) use a hand-collected dataset of European VC deals and the trust proxy is from Eurobarometer survey to examine the effect of trust in VC investment decisions. This study extends Bottazzi et al. (2016) findings by using novel data, the SCI index from Facebook user connections to quantify the social connectedness between countries and globally VC investments from Eikon. The SCI index data enable this research to analyse directly empirical relationship between social connectedness and VC investments decisions and performance. More importantly, this study assesses the relationship between social connectedness and innovation outcomes in cross-border VC investments, contributing to corporate innovation literature. In addition, this study complements the study by Gompers et al. (2016), which examines the cost of friendship in domestic VC decisions. This study incorporates the role of cross-border VCs in investment success, highlighting that homophily deteriorates investments success.

Chapter 5 analyse the role of climate risk in cross-border VC investments. With the rising recognition of climate change and its impact, investors have begun to adjust their behaviour in response to climate change (Dyck et al., 2019; Krueger et al., 2020). Although investors acknowledge climate risks, the risks perceived by investors are not the same as the actual risks. There is a strand of research of on experiential learning and behavioural bias in environment issues (Choi et al., 2020; Alok et al., 2020; Fich and Xu, 2025). Alok et al. (2020) examine mutual fund managers assets allocations after affected by natural disasters. They demonstrate that managers in disaster-affected regions are more likely to invest in other unaffected regions than managers without exposure to disasters, due to salience bias. Building on this, Chapter 5 extends this study and provides new evidence of cross-border VC investments allocations and the impact of climate risks on investments exits performance.

Using global VC investments from 1996 to 2021 and country-year level climate risks proxy from Germanwatch and ND-GAIN, this study examines cross-border VCs' strategies on investments, responding to climate risks. First, I test the role of climate risks on cross-border VC investments selections, using probit regression and the results suggest that VC investors from high climate risk countries are more likely to make cross-border investments, consistent with salience bias. Second, I assess the physical risks on cross-border VC investment exit outcomes with probit estimations and discover that greater physical risks decrease successful exits. Third, this study analyses transition risks on investments performance, measured by Readiness, which quantify the adaptive ability of each country provided by ND-GAIN. The estimated results of probit models show that readiness has positive significant impact on successful exits, which means lower transition risks of the investee company country increase cross-border VC successful exits.

Moreover, this study conducts a range of robustness tests to address endogeneity concerns. This study implements stacked DiD, with heatwaves as the climate disaster events and creates clean control groups to investigate the cross-border investments weight change in VC investors' portfolios, the empirical findings report that no significant portfolio changes until the heatwave hits. VCs investors increase cross-border VC investments allocation after exposed in heatwaves. The results are consistent with the baseline findings, VC investors originate from high climate risk countries are more prone to make cross-border investments. In addition, this study employs Heckman two stage mode with the instrument variable, country-year-level data of population density, to mitigate omitted variable concerns in exit outcomes. After higher population's effect on climate risks, the results remain robust and show that greater physical risks reduce the successful exits rates. I also apply Cox hazard model further examine the negative impact of physical risks on investment success exits. The results confirm the findings that greater physical risks reduce the probability of successful exits and prolongs the time to exit. More importantly, this study uses alternative measures and lagged indicators to evaluate the effects and address reverse casualty, and the estimation results are consistent with baseline results and confirm the findings.

Overall, these findings in Chapter 6 reveal the influence of climate risks on cross-border VC investments strategies and the ultimate exits performance of the investments and make three major contributions to the literature. First, this research contributes to climate finance literature, especially investor response on climate risk. Previous literatures illustrate that the investors recognize that climate change risks have significant impact on economic and finance (Krueger et al., 2020; Stroebel and Wergler, 2021). Huang et al. (2024) show that U.S. VCs reduce exposure to climate risks with less investments in disaster zone, and the disasters negatively influence VC exits. Second, this research extends their findings by assessing the role of climate risk in cross-border VC investments and contributes to cross-border VC literatures. Third, this research contributes to cross-country studies that focus on understanding of climate related behaviours. This study provides the first evidence that greater home-country climate risks lead to VCs' assets allocation toward cross-border, lower risks markets. In addition, this research employs a rigorously identification to establish the causality between climate risks and both VC deal selection and firm performance, offering a comprehensive understanding of the role of climate risk on cross-border VC investments and its relevance for sustainable entrepreneurship.

6.2 Implications and Recommendations for Practice

Taken together, the three empirical chapters of this thesis improve our understanding of what drive cross-border VC investments, success, and innovation. This has potential implications for capital market participants, policymakers, and entrepreneurs. The findings of Chapter 3 highlight that cross-border VC investors are important role to promote innovation. From a practical perspective, such findings are particularly beneficial for policymakers and entrepreneurs, who should recognize the value of cross-border investments in driving innovation, particularly in emerging markets. For entrepreneurs in low-innovation countries, attracting cross-border VCs could be a strategic pathway to gaining access to cutting-edge technologies and expertise, which could substantially boost their own innovation capacities. Chapter 3 further highlights the increasing significance of cross-border investment flows within a globalized economy and their role in enhancing the competitiveness of firms in the global market. It emphasizes the need for businesses to engage in international partnerships not only to secure capital but also to facilitate the exchange of knowledge and resources that can accelerate their growth. Additionally, the findings underscore the pivotal role of high-innovation countries as sources of knowledge diffusion, enabling firms in lower-innovation regions to advance more rapidly through strategic investments and technological exchanges.

Furthermore, findings of Chapter 4 provide a meaningful understanding of the broader impact of social connectedness on cross-border VC investment strategies, portfolio company success, and innovation. The findings are important for VC investors and entrepreneurs and the implications are twofold. VC investors should recognize the dual influence of social connectedness in both leading cross-border flows and shaping their ultimate success and innovation outcomes and weight both the benefits and frictions of close social connectedness when selecting cross-border VC investments opportunities. On the one hand, efficient communication and trust building from close social connectedness is favorable for innovation. On the other hand, familiarity bias and the costs of close social connectedness reduce the likelihood of successful exits. In addition, entrepreneurs could learn from the findings that they are more likely to attract capital from countries that they are more socially connected to their own.

Findings from Chapter 5 underscore the influence of climate risks on cross-border VC investment strategies and exit outcomes. These results are relevant to regulators, researchers, and investors. Policymakers should reinforce and increase adaptation capacity to enhance market resilience to climate risks. In addition, VC investors should incorporate physical and transition risks into screening, pricing, syndication, and exit planning, especially in high-risk countries.

6.3 Limitations

The main limitation of this thesis relates to the unavailability of VC investment detailed financial data. Although the measurement provides a suitable approximation of VC fund returns, and it is widely adopted for assessing VC performance, as capital gains for VC firms predominantly arise from IPOs or acquisitions (Devigne et al., 2013; Cumming et al., 2016; Dai and Nahata, 2016; Liu et al., 2021), the thesis is unable to examine the detailed impact on financial performance, such as revenues and profits. Buchner et al. (2018) use data from Centre of Private Equity Research (CEPRES), which provides detailed information on cash flow at the level of individual VC investments and quantifies the investment returns. Analysing VC investment performance with these detailed data would substantially improve understanding of financial returns and value creation.

Another limitation is that the SCI measure used in this thesis is time-invariant. Although social connectedness is likely to be relatively stable over long periods (Nguyen et al., 2023), a time-varying index would better capture changes in social proximity over time. Moreover, future research could validate this measure using alternative data sources, such as LinkedIn or other professional online platforms, which may offer a more direct proxy for economically relevant social connections.

6.4 Directions for Future Research

For future researchers, this thesis offers several avenues for extension. First, this study has assessed the impact of general regional connectedness on cross-border VC investment selections and outcomes. However, the impact of interpersonal connections on cross-border VC investments have not been examined. Future work could trace CEO relationships, board interconnections, and investors networks to uncover micro-level mechanisms. Second, investment outcomes are measured up to IPO or acquisition. However, many VCs remain engaged thereafter. It would be fruitful to evaluate the impact of cross-border VC investors the post-exit effect, such as post-IPO performance, innovation, and survival. Third, building on Chapter 5's evidence on climate risk and cross-border VCs, a potential direction for future research is to investigate the role of climate risks on other type of investments, such as corporate venture capital or VC syndication. Moreover, this thesis does not examine heterogeneous effects across different VC types, countries, and deal characteristics in a systematic way. The impact of cross-border VC investment may differ by investor reputation, experience, and size, as well as by host-country institutions, market development, industry, deal stage, and syndication structure. Exploring these dimensions would help future research better identify the channels and boundary conditions of the main results. I hope that this thesis motivates other researchers to explore this important piece of the puzzle.

Chapter 7: Reference

Abraham, J., Olbert, M., Vasvari, F. 2024. ESG disclosures in the private equity industry. *Journal of Accounting Research*, 62(5), pp.1611-1660.

Addoum, J.M., Ng, D.T., Ortiz-Bobea, A. 2023. Temperature shocks and industry earnings news. *Journal of Financial Economics*, 150(1), pp.1-45.

Admati, A.R., Pfleiderer, P. 1994. Robust Financial Contracting and the Role of Venture Capitalists. *The Journal of Finance*, 49: 371-402.

Aghion, P., Howitt, P. 1992. A Model of Growth Through Creative Destruction. *Econometrica*, 60 (2), pp. 323-351.

Agrawal, A., Kapur, D., McHale, J. 2008. How do spatial and social proximity influence knowledge flows? Evidence from patent data. *Journal of Urban Economics*, 64(2), pp.258-269.

Almeida, H., Fos, V., Hsu, P.H., Kronlund, M., Tseng, K. 2024. Innovation under pressure. *Journal of Financial and Quantitative Analysis*, pp.1-53.

Alok, S., Kumar, N. and Wermers, R. 2020. Do fund managers misestimate climatic disaster risk. *The Review of Financial Studies*, 33(3), pp.1146-1183.

Akcigit U, Ates ST., Lerner J, Townsend RR, Zhestkova Y. 2024. Fencing off Silicon Valley: Cross-border venture capital and technology spillovers. *Journal of Monetary Economic*s. 141, pp.14-39.

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

Amini, S., Mohamed, A., Schwienbacher, A. and Wilson, N. 2022. Impact of venture capital holding on firm life cycle: evidence from IPO firms. *Journal of Corporate Finance*, 74, p.102224.

Amore, M.D., Schneider, C., Žaldokas, A., 2013. Credit supply and corporate innovation. *Journal of Financial Economics*, 109(3), pp. 835-855.

An, H., Chen, C.R., Wu, Q., Zhang, T. 2021. Corporate innovation: Do diverse boards help? *Journal of Financial and Quantitative Analysis*, 56(1), pp.155-182.

Andre, P., Boneva, T., Chopra, F. and Falk, A. 2024. Misperceived social norms and willingness to act against climate change. *Review of Economics and Statistics*, pp.1-46.

Babina, T., Fedyk, A., He, A., Hodson, J. 2024. Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151, p.103745.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., Wong, A. 2018a). Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives*, 32(3), pp.259-280.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J. 2018b. The economic effects of social networks: Evidence from the housing market. *Journal of Political Economy*, 126(6), pp.2224-2276.

Bailey, M., Gupta, A., Hillenbrand, S., Kuchler, T., Richmond, R. and Stroebel, J. 2021. International trade and social connectedness. *Journal of International Economics*, 129, p.103418.

Bailey, M., Johnston, D., Kuchler, T., Russel, D., State, B., Stroebel, J. 2020. The determinants of social connectedness in Europe. In Social Informatics: 12th International Conference, SocInfo 2020, Pisa, Italy, October 6–9, 2020, Proceedings 12 (pp. 1-14). Springer International Publishing.

Baker, A.C., Larcker, D.F., Wang, C.C. 2022. How much should we trust staggered difference-in-differences estimates?. *Journal of Financial Economics*, 144(2), pp.370-395.

Bansal, R., D. Kiku, M. Ochoa. 2016. Price of long-run temperature shifts in capital markets. Working Paper.

Baranchuk, N., Kieschnick, R., Moussawi, R. 2014. Motivating innovation in newly public firms. *Journal of Financial Economics*, *111*(3), pp.578-588.

Barber, B.M., Morse, A., Yasuda, A. 2021. Impact investing. *Journal of Financial Economics*, 139(1), pp.162-185.

Barnett, M. 2023. Climate change and uncertainty: An asset pricing perspective. *Management Science*, 69(12), pp.7562-7584.

Barney, J. 1986. Organizational culture: Can it be a source of sustained competitive advantage? *The Academy of Management Review*, 11(3), pp. 656–665.

Barney, J. 1991. Firm resources and sustained competitive advantage. *Journal of Management,* 17(1), pp. 99–120.

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

Bartram, S.M., Hou, K. and Kim, S. 2022. Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics*, 143(2), 668-696.

Baum, J. A. C., Silverman, B. S. 2004. Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. *Journal of Business Venturing*, 19(3), 411–436.

Baygan, G., Freudenberg, M. 2000. The Internationalisation of Venture Capital Activity in OECD Countries: Implications for Measurement and Policy. *OECD Science, Technology and Industry Working Papers, OECD Publishing.*

Bena, J., Ferreira, M., Matos, P., Pires, P. 2017. Are foreign investors locusts? The long-term effects of foreign institutional ownership. *Journal of Financial Economics*, 126 (1), 122-146.

Benson, D., Ziedonis, R.H. 2010. Corporate venture capital and the returns to acquiring portfolio companies. *Journal of Financial Economics*, 98, pp. 478-499.

Berk, J.B., Van Binsbergen, J.H. 2025. The impact of impact investing. *Journal of Financial Economics,* 164, p.103972.

Bernile, G., Bhagwat, V., Kecskés, A., Nguyen, P.A. 2021. Are the risk attitudes of professional investors affected by personal catastrophic experiences?. *Financial management*, 50(2), pp.455-486.

Bernile, G., Bhagwat, V., Rau, P.R. 2017. What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior. *The Journal of Finance*, 72(1), pp.167-206.

Bernstein, A., Gustafson, M.T. and Lewis, R. 2019. Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, 134(2), pp.253-272.

Bernstein, S., Giroud, X., Townsend, R. 2016. The Impact of Venture Capital Monitoring. *The Journal of Finance*, 71(4), pp. 1591-1622.

Black, B.S. and Gilson, R.J. 1998. Venture capital and the structure of capital markets: banks versus stock markets. *Journal of Financial Economics*, 47(3), pp.243-277.

Block, J. H., Vries, D. G., Schumann, J. H., Sandner, P. 2014. Trademarks and venture capital valuation. *Journal of Business Venturing*, 29 (4), pp. 525-542.

Block, J., Fisch, C., Vismara, S., Andres, R. 2019. Private equity investment criteria: An experimental conjoint analysis of venture capital, business angels, and family offices. *Journal of corporate finance*, *58*, pp.329-352.

Block, J.H., Hirschmann, M., Fisch, C. 2021. Which criteria matter when impact investors screen social enterprises?. *Journal of Corporate Finance,* 66, p.101813.

Bolton, P., Kacperczyk, M. 2023. Global pricing of carbon-transition risk. *The Journal of Finance,* 78(6), pp.3677-3754.

Bolton, P., Kacperczyk, M.T. 2021. Carbon disclosure and the cost of capital. Available at SSRN 3755613.

Bonelli, M. 2025. Data-driven investors, *The Review of Financial Studies*.

Bordalo, Gennaioli, Shleifer 2012, Salience theory of choice under risk, *The quarterly journal of economics.*

Bordalo, P., Gennaioli, N., Shleifer, A. 2013. Salience and consumer choice. *Journal of Political Economy*, 121(5), pp.803-843.

Boryniec, T., Li, C., Tan, Y. 2023. A survey of cross-border venture capital research. *Venture Capital*, pp.1-62.

Bottazzi, L., Da Rin, M., Hellmann, T. 2008. Who are the active investors?: Evidence from venture capital. *Journal of financial economics*, *89*(3), pp.488-512.

Bottazzi, L., Da Rin, M., Hellmann, T. 2016. The importance of trust for investment: Evidence from venture capital. *The Review of Financial Studies*, 29(9), pp.2283-2318.

Boud, D., R. Keogh, D. Walker. 1985. Reflection: Turning experience into learning. London: Routledge Falmer.

Bosio, A.O., Buttice, V., Crisanti, A., Croce, A., Signore, S., 2025. How Brexit reshaped venture capitals market: An analysis of UK and EU investments. *Research Policy*, 54(8), p.105289.

Brander, J.A., Amit, R., Antweiler, W. 2002. Venture-capital syndication: improved venture selection vs. the value-added hypothesis. *Journal of Economics & Management Strategy*, 11 (3), pp. 423–452.

Brown, J.R., Martinsson, G. 2019. Does transparency stifle or facilitate innovation? *Management Science*, 65(4), pp.1600-1623.

Brown, J.R., Martinsson, G., Thomann, C. 2022. Can environmental policy encourage technical change? Emissions taxes and R&D investment in polluting firms. *The Review of Financial Studies*, 35(10), pp.4518-4560.

Bruton, G. D., Fried, V. H., Manigart, S. 2005. Institutional Influences on the Worldwide Expansion of Venture Capital. *Entrepreneurship Theory and Practice*, *29*(6), pp. 737-760.

Bubna, A., Das, S., Prabhala, N. 2020. Venture Capital Communities. *Journal of Financial and Quantitative Analysis*, 55(2), pp. 621-651.

Buchner, A., Espenlaub, S., Khurshed, A., Mohamed, A. 2018. Cross-border venture capital investments: The impact of foreignness on returns. *Journal of International Business Studies*, 49, pp. 575-604.

Bulter, J. E. 1988. Theories of technological innovation as useful tools for corporate strategy. *Strategic Management Journal*, 5(1), pp.15-29.

Cai, Y., Pan, C.H., Statman, M. 2016. Why do countries matter so much in corporate social performance?. *Journal of Corporate Finance*, 41, pp.591-609.

Cai, Y., Sevilir, M. 2012. Board connections and M&A transactions. Journal of Financial Economics, 103(2), pp.327-349.

Ceccarelli, M., Ramelli, S., Wagner, A.F. 2024. Low carbon mutual funds. *Review of Finance*, 28(1), pp.45-74.

Cengiz, D., Dube, A., Lindner, A., Zipperer, B. 2019. The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics, 134(3), pp.1405-1454.*

Chahine, S., Goergen, M., Saade, S. 2022. Foreign Venture Capitalists and access to foreign research: the case of US Initial Public Offering. *British Journal of Management,* 33(1), pp. 160-180.

Chandler, G. N., Hanks, S. H. 1994. Market attractiveness, resource-based capabilities, venture strategies, and venture performance. *Journal of Business Venturing*, 9(4), pp. 331–349.

Chaney, T. 2016. Networks in international trade. The Oxford Handbook of The Economics of Networks.

Chang, T., W. Huang, and Y. Wang. 2018. Something in the air: Pollution and the demand for health insurance. *Review of Economic Studies*, 85:1609–34.

Chava, S. 2014. Environmental externalities and cost of capital. *Management Science*, 60(9), pp.2223-2247.

Chemmanur, T. J., Kong, L., Krishnan, K., Yu, Q. 2019. Top management human capital, inventor mobility, and corporate innovation. *Journal of Financial and Quantitative Analysis,* 54(6), 2383-2422.

Chemmanur, T. J., Loutskina, E., Tian, X. 2014. Corporate Venture Capital, Value Creation, and Innovation. *The Review of Financial Studies*, 27(8), 2434-2473.

Chemmanur, T., Hull, T., Krishnan, K. 2020. Cross-Border LBOs, Human Capital, and Proximity: Value Addition through Monitoring in Private Equity Investments. *Journal of Financial and Quantitative Analysis*, 56(3), pp. 1023–1063.

Chemmanur, T., Krishnan, K., Nandy,K. 2011. How Does Venture Capital Financing Improve Efficiency in Private Firms? A Look Beneath the Surface. *Review of Financial Studies*, 24(12), pp. 4037-4090.

Chemmanur, T., Loutskina, E., Tian, X. 2014. Corporate Venture Capital, Value Creation, and Innovation. *Review of Financial Studies*, 27(8), pp. 2434–2473.

Chemmanur, T.J., Hull, T.J., Krishnan, K. 2016. Do local and international venture capitalists play well together? The complementarity of local and international venture capitalists. *Journal of Business Venturing*, 31(5), pp.573-594.

Chemmanur, T.J., Krishnan, K., Nandy, D.K. 2011. How does venture capital financing improve efficiency in private firms? A look beneath the surface. *The Review of Financial Studies,* 24(12), pp.4037-4090.

Chen, H., Gompers, P., Kovner, A., Lerner, J. 2010. Buy local? The geography of venture capital. *Journal of Urban Economics*, 67(1), pp.90-102.

Chen, J. and Roth, J., 2024. Logs with zeros? Some problems and solutions. *The Quarterly Journal of Economics*, 139(2), pp.891-936.

Chen, J., Leung, W.S., Evans, K.P. 2018. Female board representation, corporate innovation and firm performance. *Journal of Empirical Finance*, 48, pp.236-254.

Chen, J., Roth, J. 2024. Logs with zeros? Some problems and solutions. *The Quarterly Journal of Economic*s, 139(2), pp.891-936.

Choi, D., Gao, Z., Jiang, W. 2020. Attention to global warming. *The Review of Financial Studies,* 33(3), pp.1112-1145.

Choudhury, P. 2022. Geographic mobility, immobility, and geographic flexibility: A review and agenda for research on the changing geography of work. *Academy of Management Annals,* 16(1), pp.258-296.

Ciccarelli, M., Marotta, F. 2024. Demand or supply? An empirical exploration of the effects of climate change on the macroeconomy. *Energy Economics*, 129, p.107163.

Cohen, B. 2006. Sustainable valley entrepreneurial ecosystems. *Business Strategy and the Environment*, 15(1), pp.1-14.

Cohen, B., Winn, M.I. 2007. Market imperfections, opportunity and sustainable entrepreneurship. *Journal of Business Venturing*, 22(1), pp.29-49.

Cohen, L., Frazzini, A., Malloy, C. 2008. The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy*, 116(5), pp.951-979.

Cohen, S., Kadach, I., Ormazabal, G. 2023. Institutional investors, climate disclosure, and carbon emissions. *Journal of Accounting and Economics*, 76(2-3), p.101640.

Cohn, J. B., Liu, Z., Wardlaw, M. I. 2022. Count (and count-like) data in finance. *Journal of Financial Economics*, 146(2), pp.529-551.

Cohn, J.B., Wardlaw, M.I., 2016. Financing constraints and workplace safety. J*ournal of Finance,* 71 (5), pp. 2017-2058.

Cole, S., Jeng, L., Lerner, J., Rigol, N., Roth, B.N. 2023. What do impact investors do differently? (No. w31898). National Bureau of Economic Research.

Colombo, M.G., Dagnino, G.B., Lehmann, E.E., Salmador, M. 2019. The governance of entrepreneurial ecosystems. *Small Business Economics*, 52, pp.419-428.

Cong, L., Xiao, Y. 2022. Persistent Blessings of Luck: Theory and an Application to Venture Capital. *Review of Financial Studies*, 35(3), pp. 1183-1221.

Conti, A., Graham, S.J. 2020. Valuable choices: prominent venture capitalists' influence on startup CEO replacements. *Management Science*, 66(3), pp.1325-1350.

Cooper, A. C., Gimenogascon, F. J., Woo, C. Y. 1994. Initial human and financial capital as predictors of new venture performance. *Journal of Business Venturing*, 9(5), pp. 371–395.

Coval, J., Moskowitz, T. 1999. Home bias at home: local equity preference in domestic portfolios. The Journal of Finance 54, 2045–2073.

Cowling, M., Brown, R. 2024. Intra-and interregional flows of business angel investment: mapping the winners and losers across UK regions and core urban economies. *Regional Studies,* pp.1-15.

Crosby, L. A., Evans, K. R., Cowles, D. 1990. Relationship quality in services selling: An interpersonal influence perspective. *Journal of Marketing*, 54, pp.68–81.

Cumming, D. 2008. Contracts and exits in venture capital finance. *The Review of Financial Studies*, 21(5), pp.1947-1982.

Cumming, D. J., Knill, A., Syvrud, K. 2016. Do international investors enhance private firm value? Evidence from venture capital. *Journal of International Business Studies*, 47(3), pp.347-373.

Cumming, D., Dai, N. 2010. Local bias in venture capital investments. *Journal of Empirical Finance*, 17(3), pp. 362-380.

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

Cumming, D., Fleming, G., Schwienbacher, A. 2009. Corporate relocation in venture capital finance. *Entrepreneurship Theory and Practice*, 33, pp. 1121–1155.

Cumming, D., Henriques, I., Sadorsky, P. 2016. 'Cleantech' venture capital around the world. *International Review of Financial Analysis*, 44, pp.86-97.

Cumming, D., Knill, A., Syvrud, K. 2016. Do international investors enhance private firm value? Evidence from venture capital. *Journal of International Business Studies*, 47(3), pp. 347-373.

Cumming, D., Zhang, M. 2019. Angel investors around the world. *Journal of International Business Studies*, *50*, pp.692-719.

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

Dai, N., Nahata, R. 2016 Cultural differences and cross-border venture capital syndication. *Journal of International Business Studies*, 47(2), pp.140-169.

Dasgupta, S., Huynh, T.D., Xia, Y. 2023. Joining forces: The spillover effects of EPA enforcement actions and the role of socially responsible investors. *The Review of Financial Studies,* 36(9), pp.3781-3824.

De Prijcker, S., Manigart, S., Wright, M., De Maeseneire, W. 2012. The influence of experiential, inherited and external knowledge on the internationalization of venture capital firms. *International Business Review*, 21(5), pp.929-940.

Deng, X., Li, Q., Mateut, S. 2022. Participation in setting technology standards and the implied cost of equity. *Research Policy*, 51(5), 104497.

Dessaint, O., Matray, A. 2017. Do managers overreact to salient risks? Evidence from hurricane strikes. *Journal of Financial Economics*, 126(1), pp.97-121.

Devigne, D., Manigart, S., Wright, M. 2016. Escalation of commitment in venture capital decision making: Differentiating between domestic and international investors, *Journal of Business Venturing*, 31 (3), pp. 253-271.

Devigne, D., Vanacker, T., Manigart, S., Paeleman, I. 2013. The role of domestic and cross-border venture capital investors in the growth of portfolio companies. *Small Business Economics*, 40(3), pp. 553–573.

Di Giuli, A., Kostovetsky, L. 2014. Are red or blue companies more likely to go green? Politics and corporate social responsibility. *Journal of Financial Economics*, 111(1), pp.158-180.

Dimmock, S. G., Gerken, W. C., Graham, N. P. 2018. Is fraud contagious? Coworker influence on misconduct by financial advisors. *Journal of Finance*,73(3), pp.1417–1450.

Doerr, S. 2021. Stress Tests, Entrepreneurship, and Innovation, *Review of Finance*, 25(5), pp. 1609–1637.

Dong, R., Fisman, R., Wang, Y., Xu, N. 2021. Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts. *Journal of Financial Economics*, 139(3), pp.971-984.

Dow, D., Karunaratna, A. 2006. Developing a multidimensional instrument to measure psychic distance stimuli. *Journal of International Business Studies*, *37*, pp.578-602.

Downey, M., Lind, N., Shrader, J.G. 2023. Adjusting to rain before it falls. *Management Science*, 69(12), pp.7399-7422.

Duchin, R., Gao, J., Xu, Q. 2025. Sustainability or greenwashing: Evidence from the asset market for industrial pollution. *The Journal of Finance*, 80(2), pp.699-754.

Duggan, M., Ellison, N.B., Lampe, C., Lenhart, A., Madden, M. 2015. Social media update 2014. *Pew Research Center*, 19(1), pp.1-2.

Dyck, A., Lins, K.V., Roth, L., Wagner, H.F. 2019. Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics*, 131(3), pp.693-714.

Eckstein, D., Künzel, V., Schäfer, L. 2021. The global climate risk index 2021. Bonn: Germanwatch.

Ederer, F., Manso, G. 2013. Is Pay for Performance Detrimental to Innovation? *Management Science*, 59(7), pp. 1496–1513.

Eldar, O., Grennan, J. 2024. Common venture capital investors and startup growth, *The Review of Financial Studies*, 37(2), pp. 549–590.

Ertug, G., Brennecke, J., Kovács, B., Zou, T. 2022. What does homophily do? A review of the consequences of homophily. *Academy of Management Annals*, 16(1), pp.38-69.

Espenlaub, S., Khurshed, A., Mohamed, A. 2015. Venture capital exits in domestic and cross-border investments. *Journal of Banking and Finance*, 53, pp. 215-232.

Ewens, M., Farre-Mensa, J. 2022. Private or public equity? The evolving entrepreneurial finance landscape. *Annual Review of Financial Economics*, 14(1), pp.271-293.

Ewens, M., Gorbenko, A., Korteweg, A. 2022. Venture capital contracts. *Journal of Financial Economics*, 143(1), 131-158.

Ewens, M., Marx, M. 2018. Founder replacement and startup performance. *The Review of Financial Studies*, 31(4), pp.1532-1565.

Ewens, M., Townsend, R. R. 2020. Are early stage investors biased against women? *Journal of Financial Economics*,135(3), pp. 653–677.

Farida, S., Fidrmuc, J.P., Zhang, C. 2025. M&As and innovation: Evidence from acquiring private firms. *Journal of Corporate Finance*, p.102905.

Feldhutter, P., Halskov, K., Krebbers, A. 2024. Pricing of sustainability-linked bonds. *Journal of Financial Economics*, 162, p.103944.

Fich, E.M., Xu, G. 2025. Do salient climatic risks affect shareholder voting?. *Review of Finance,* 29(2), pp.567-602.

Foroughi, P., Marcus, A., Nguyen, V. 2024. Mutual fund pollution experience and environmental voting. *Journal of Banking & Finance*, 162, p.107149.

Freeman, R.B. and Huang, W. 2015. Collaborating with people like me: Ethnic coauthorship within the United States. *Journal of Labor Economics*, 33(S1), pp.S289-S318.

Frésard, L., Hoberg, G., Phillips, G. 2020. Innovation Activities and Integration through Vertical Acquisitions. *Review of Financial Studies*, 33(7), pp. 2937–2976.

Gerarden, T.D. 2023. Demanding innovation: The impact of consumer subsidies on solar panel production costs. *Management Science*, 69(12), pp.7799-7820.

Giglio, S., Maggiori, M., Stroebel, J., Tan, Z., Utkus, S., Xu, X. 2025. Four facts about ESG beliefs and investor portfolios. *Journal of Financial Economics*, 164, p.103984.

Gillan, S., Starks, L. 2003. Corporate Governance, Corporate Ownership, and the Role of Institutional Investors: A Global Perspective. *Journal of Applied Finance,* 13, pp. 4–22.

Gilly, M.C., Graham, J.L., Wolfinbarger, M.F., Yale, L.J. 1998. A dyadic study of interpersonal information search. *Journal of the Academy of Marketing Science*, 26(2), pp.83-100.

Ginglinger, E., Moreau, Q. 2023. Climate risk and capital structure. *Management Science*, 69(12), pp.7492-7516.

Giot, P., Schwienbacher, A. 2007. IPOs, trade sales and liquidation: modelling venture capital exits using survival analysis. *Journal of Banking & Finance*, 31, 697–702.

Glaeser, E.L. 1999. Learning in cities. *Journal of urban Economics*, 46(2), pp.254-277.
Goetzmann, W.N., Kim, D., Kumar, A., Wang, Q. 2015. Weather-induced mood, institutional investors, and stock returns. *The Review of Financial Studies*, 28(1), pp.73-111.

Gompers, P. 2002. Corporations and the financing of innovation: The corporate venturing experience. *Economic Review, Federal Reserve Bank of Atlanta*, 87(Q4), pp. 1-17.

Gompers, P., 1995. Optimal investment, monitoring, and the staging of venture capital. *The Journal of Finance*, 50 (5), pp. 1461–1489.

Gompers, P., Gornall, W., Kaplan, S. N., Strebulaev, I. A. 2020. How do venture capitalists make decisions? *Journal of Financial Economics*, 135(1), pp. 169-190.

Gompers, P., Kovner, A., Lerner, J., Scharfstein, D. 2005. Venture capital investment cycles: The role of experience and specialization. *Journal of Financial Economics*, 81(1), pp.649-679.

Gompers, P., Lerner, J. 1998. The Venture Capital Revolution. *The Journal of Economic Perspectives*, 15(2), pp. 145-168.

Gompers, P., Lerner, J. 1998. Venture capital distributions: Short-run and long-run reactions. *The Journal of Finance*, 53(6), pp.2161-2183.

Gompers, P.A., Mukharlyamov, V., Xuan, Y. 2016. The cost of friendship. *Journal of Financial Economics*, 119(3), pp.626-644.

González-Uribe, J. 2020. Exchanges of innovation resources inside venture capital portfolios. *Journal of Financial Economics*, 135, pp. 144-168.

González-Uribe, J., Klingler-Vidra, R., Wang, S., Yin, X. 2026. The broader role of venture capital due diligence, *The Review of Financial Studies*. p.hhag014.

Gorman, M., Sahlman, W. 1989. What do venture capitalists do? *Journal of Business Venturing*, 4, pp. 231–248.

Gornall, W., Strebulaev, I.A. 2015. The economic impact of venture capital: evidence from public companies. Unpublished working paper. Stanford University.

Gounopoulos, D., Zhang, Y. 2024. Temperature trend and corporate cash holdings. *Financial Management*, 53(3), pp.471-499.

Granovetter, M. 2018. The Impact of Social Structure on Economic Outcomes. In The Sociology of Economic Life (pp. 46-61). Routledge.

Greenberg, J., Mollick, E. 2017. Activist choice homophily and the crowdfunding of female founders. *Administrative Science Quarterly*, 62(2), pp.341–374.

Griliches, Z. 1990. Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, 28(4), pp. 1661-1707.

Groh, A. P., von Liechtenstein, H. 2009. How attractive is central Eastern Europe for risk capital investors? *Journal of International Money and Finance*, 28, 625–647.

Gu, Q., Lu, X., 2014. Unraveling the mechanisms of reputation and alliance formation: A study of venture capital syndication in China. *Strategic Management Journal*, 35(5), pp. 739-750.

Guadalupe, M., Kuzmina, O., Thomas, C. 2012. Innovation and foreign ownership. *American Economic Review*, 102(7), pp.3594-3627.

Guiso, L., Sapienza, P., Zingales, L. 2008. Trusting the stock market. *The Journal of Finance*, 63 (6), pp. 2557–2600.

Guiso, L., Sapienza, P., Zingales, L. 2009. Cultural biases in economic exchange? *The Quarterly Journal of Economics*, 124(3), pp.1095-1131.

Guler, I. 2007. Throwing good money after bad? political and institutional influences on sequential decision making in the venture capital industry. *Administrative Science Quarterly*, 52(2), pp. 248-285.

Guler, I., Guillen, M.F. 2010. Home country networks and foreign expansion: evidence from the venture capital industry. *The Academy of Management Journal*, 53 (2), pp. 390–410.

Guler, I., Guillén, M.F. 2010. Institutions and the internationalization of US venture capital firms. *Journal of International Business Studies*, *41*, pp.185-205.

Hain, D., Johan, S., Wang, D. 2016. Determinants of cross-border venture capital investments in emerging and developed economies: The effects of relational and institutional trust. *Journal of Business Ethics*, 138, pp.743-764.

Hall, B. H., Jaffe, A. B., Trajtenberg, M. 2001. The NBER patent citation data file: Lessons, insights and methodological tools. *NBER Working Paper*.

Han, P., Liu, C., Tian, X., Wang, K., 2026. Invest local or remote? The effects of COVID-19 lockdowns on venture capital investment around the world. *Management Science*, 72(4), pp.3351-3370.

Harris, R.S., Jenkinson, T., Kaplan, S.N. 2014. Private equity performance: What do we know?. *The Journal of Finance*, *69*(5), pp.1851-1882.

Hausman, J., Hall, B., Griliches, Z. 1984. Econometric models for count data and an application to the patents - R&D relationship. *Econometrica*, 52, pp. 909-938.

He, J.J., Tian, X. 2013. The dark side of analyst coverage: The case of innovation. *Journal of Financial Economics*, 109(3), pp.856-878.

He, Q., Qiu, B. 2025. Environmental enforcement actions and corporate green innovation. *Journal of Corporate Finance*, 91, p.102711.

He, Z., Hirshleifer, D. 2022. The exploratory mindset and corporate innovation. *Journal of Financial and Quantitative Analysis*, 57(1), pp.127-169.

Heckman, J. J. 1979). Sample selection bias as a specification error. *Econometrica: Journal of the Econometric Society,* pp.153-161.

Heeb, F., Kölbel, J.F., Paetzold, F., Zeisberger, S. 2023. Do investors care about impact?. *The Review of Financial Studies*, 36(5), pp.1737-1787.

Hellmann, T., Puri, M. 2000. The interaction between product market and financing strategy: the role of venture capital. *The Review of Financial Studies*, 13(4), pp. 959-984.

Hellmann, T., Puri, M. 2002. Venture capital and the professionalization of start-up firms: Empirical evidence. *The Journal of Finance*, *57*(1), pp.169-197.

Hirshleifer, D. and Shumway, T. 2003. Good day sunshine: Stock returns and the weather. *The Journal of Finance*, 58(3), pp.1009-1032.

Hirshleifer, D., Low, A., Teoh, S. 2012. Are Overconfident CEOs Better Innovators? The Journal of Finance, 67(4), pp. 1457-1498.

Hirshleifer, D., Peng, L., Wang, Q. 2024. News diffusion in social networks and stock market reactions. *The Review of Financial Studies*, hhae025.

Hochberg, Y. V., Ljungqvist, A., Lu, Y. 2007. Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance,* 62(1), 251-301.

Hoenen, S., C. Kolympiris, W. Schoenmakers, N. Kalaitzandonakes. 2014. The Diminishing Signaling Value of Patents Between Early Rounds of Venture Capital Financing. *Research Policy*, 43 (6), pp. 956–989.

Hoepner, A.G., Oikonomou, I., Sautner, Z., Starks, L.T., Zhou, X.Y. 2024. ESG shareholder engagement and downside risk. *Review of Finance*, 28(2), pp.483-510.

Holmstrom, B. 1989. Agency Costs and Innovation. *Journal of Economic Behavior and Organization*, 12, pp. 67–93.

Hong, H., Li, F.W., Xu, J. 2019. Climate risks and market efficiency. *Journal of Econometrics*, 208(1), pp.265-281.

Hou, K., Hsu, P-H., Wang, S., Watanabe, A., Xu, Y. 2022. Corporate R&D and Stock Returns: International Evidence. *Journal of Financial and Quantitative Analysis*, 57 (4), pp. 1377-1408.

Howell, S.T. 2020. Reducing information frictions in venture capital: The role of new venture competitions. *Journal of Financial Economics*, 136(3), pp.676-694.

Hsu, P., Huang, P., Humphery-Jenner, M. Powell, R. 2021. Cross-border mergers and acquisitions for innovation. *Journal of International Money and Finance*, 112, 102320.

Hsu, P., Tian, X., Xu, Y. 2014. Financial development and innovation: Cross-country evidence. *Journal of Financial Economics*, 112(1), pp. 116-135.

Hsu, P.H., Li, K. and Tsou, C.Y. 2023. The pollution premium. *The Journal of Finance*, 78(3), pp.1343-1392.

Hsu, P.H., Lü, Y., Wu, H., Xuan, Y. 2024. Director job security and corporate innovation. *Journal of Financial and Quantitative Analysis*, 59(2), pp.652-689.

Huang, C., Zhang, A., Zhang, M. and Zhao, Y. 2025. Venture capital and vulnerability: Navigating natural disasters and investment resilience. *European Financial Management*, 31(3), pp.1124-1147.

Huang, H.H., Kerstein, J., Wang, C. 2018. The impact of climate risk on firm performance and financing choices: An international comparison. *Journal of International Business Studies*, 49(5), pp.633-656.

Huang, H.H., Kerstein, J., Wang, C., Wu, F. 2022. Firm climate risk, risk management, and bank loan financing. *Strategic Management Journal*, 43(13), pp.2849-2880.

Huang, J., Xu, N., Yu, H. 2020. Pollution and performance: Do investors make worse trades on hazy days?. *Management Science*, 66(10), pp.4455-4476.

Humphery-Jenner, M., Suchard, J.A. 2013. Foreign VCs and venture success: Evidence from China. *Journal of Corporate Finance*, 21, pp.16-35.

Humphery-Jenner, M., Sautner, Z., Suchard, J.A. 2017. Cross-border mergers and acquisitions: The role of private equity firms. *Strategic Management Journal,* 38(8), pp.1688-1700.

Humphrey, J.E., Li, Y. 2021. Who goes green: Reducing mutual fund emissions and its consequences. *Journal of Banking & Finance*, 126, p.106098.

Ilhan, E., Krueger, P., Sautner, Z., Starks, L.T. 2023. Climate risk disclosure and institutional investors. *The Review of Financial Studies*, 36(7), pp.2617-2650.

Ilhan, E., Sautner, Z., Vilkov, G. 2021. Carbon tail risk. *The Review of Financial Studies*, 34(3), pp.1540-1571.

Intergovernmental Panel on Climate Change. 2023. Climate Change 2023 Synthesis Report. Intergovernmental Panel on Climate Change, Geneva, Switzerland.

Iriyama, K., Li, Y., Madhavan, R. 2010. Spiky globalization of venture capital investments: the influence of prior human networks. *Strategic Entrepreneurship Journal*, 4(2), pp. 128-145.

Jaasskelainen, M., Maula, M., Seppa, T. 2005. Allocation of Attention to Portfolio Companies and the Performance of Venture Capital Firms. *Entrepreneurship Theory and Practice*, 30(2), pp. 185-206.

Jaffe, A.B., Trajtenberg, M., Henderson, R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly journal of Economics*, 108(3), pp.577-598.

Jeffers, J., Lyu, T., Posenau, K. 2024. The risk and return of impact investing funds. *Journal of Financial Economics*, 161, p.103928.

Jia, J., Li, Z. 2020. Does external uncertainty matter in corporate sustainability performance?. *Journal of Corporate Finance*, 65, p.101743.

Kadri Ekinci, N., Alp Ertürk, K. 2007. Turkish currency crisis of 2000–2001, revisited. *International Review of Applied Economics*, 21(1), pp.29-41.

Kamstra, M.J., Kramer, L.A., Levi, M.D. 2000. Losing sleep at the market: The daylight saving anomaly. *American Economic Review,* 90(4), pp.1005-1011.

Kamstra, M.J., Kramer, L.A., Levi, M.D. 2003. Winter blues: A SAD stock market cycle. *American Economic Review*, 93(1), pp.324-343.

Kandel, E., Leshchinskii, D., Yuklea, H. 2011. VC Funds: Aging Brings Myopia. *Journal of Financial and Quantitative Analysis,* 46, 431–457.

Kaplan, S. N., Sensoy, B. A., Strömberg, P. 2009. Should Investors Bet on the Jockey or the Horse? Evidence from the Evolution of Firms from Early Business Plans to Public Companies. *The Journal of Finance*, 64(1), pp. 75-115.

Kaplan, S. N., Stromberg, P. 2004. Characteristics, Contracts, and Actions: Evidence from Venture Capitalist Analyses. *The Journal of Finance*, 59(5), pp. 2177-2210.

Kaplan, S. N., Strömberg. P. 2003. Financial contracting meets the real world: An empirical analysis of venture capital contracts. *Review of Financial Studies,* 70, pp. 281–315.

Kenney, M., Han, K., Tanaka, S. 2002. Scattering geese: the venture capital industries of East Asia: a report to the World Bank. *Berkeley Roundtable on the International Economy*, WP146, Berkeley, CA.

Khurshed, A., Mohamed, A., Schwienbacher, A., Wang, F 2020. Do venture capital firms benefit from international syndicates? *Journal of International Business Studies*, 51(6), 986-1007.

Koh, P.-S., Reeb. D. M. 2015. Missing R&D. *Journal of Accounting and Economics*, 60, pp.73–94.

Kolb, A. 1984. Experiential learning: Experience as the source of learning and development. Englewood Cliffs, NJ: Prentice Hall.

Konara, P., Batsakis, G., Shirodkar, V. 2022. “Distance” in intellectual property protection and MNEs’ foreign subsidiary innovation performance, *Journal of Product Innovation Management*, 00, pp. 1-25.

Kondo, J., Li, D., Papanikolaou, D. 2020. Trust, Collaboration, and Economic Growth. *Management Science*, 67(3), pp.1329-1992.

Kong, D., Zhao, Y., Liu, S. 2021. Trust and innovation: Evidence from CEOs' early-life experience. *Journal of Corporate Finance*, 69, p.101984.

Korteweg, A., Sorensen, M. 2010. Risk and return characteristics of venture capital-backed entrepreneurial companies. *The Review of Financial Studies*, 23(10), pp.3738-3772.

Kortum, S., Lerner, J. 2000. Assessing the contribution of venture capital to innovation. *The RAND Journal of Economics*, 31 (4), pp. 674-692.

Kreft, S., Eckstein, D. 2014. Global climate risk index 2014. Bonn: Germanwatch.

Krueger, P., Sautner, Z., Starks, L.T. 2020. The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3), pp.1067-1111.

Kruttli, M.S., Tran, B.R., Watugala, S.W. 2025. Pricing Poseidon: Extreme weather uncertainty and firm return dynamics. *The Journal of Finance*, 80(2), pp.783-832.

Kuchler, T., Li, Y., Peng, L., Stroebel, J., Zhou, D. 2022. Social proximity to capital: Implications for investors and firms. *The Review of Financial Studies*, 35(6), pp.2743-2789.

Lahr, H., Mina, A. 2016. Venture capital investments and the technological performance of portfolio firms. *Research Policy*, 45(1), pp. 303-318.

Lamperti, F., Bosetti, V., Roventini, A., Tavoni, M. 2019. The public costs of climate-induced financial instability. *Nature Climate Change*, 9(11), pp.829-833.

Lazarsfeld, P., R. K. Merton. 1954. Friendship as a Social Process: A Substantive and Methodological Analysis. In Freedom and Control in Modern Society, edited by Morroe Berger, Theodore Abel, and Charles H. Page. New York: Van Nostrand.

Lee, J., Lee, K. J., Nagarajan, N. J. 2014. Birds of a feather: Value implications of political alignment between top management and directors. *Journal of Financial Economics*,112 (2), pp.232–250

Lerner, J. 1995. Patenting in the Shadow of Competitors. *The Journal of Law and Economics*, 38(2), pp.463-495.

Lerner, J. 1995. Venture capitalists and the oversight of private firms. *Journal of Finance*, 50, pp. 301–318.

Lerner, J., Lithell, M., Phillips, G.M. 2025. Impact Investing and Worker Outcomes (No. w33611). National Bureau of Economic Research.

Lerner, J., Seru. A. 2022. The Use and Misuse of Patent Data: Issues for Finance and Beyond. *Review of Financial Studies*, 35 (6), pp. 2667–2704.

Lerner, J., Sorensen. M., Strömberg, P. 2011. Private Equity and Long-Run Investment: The Case of Innovation. *The Journal of Finance*, 66(2), pp. 445-477.

Li, J.J., Massa, M., Zhang, H., Zhang, J. 2021. Air pollution, behavioral bias, and the disposition effect in China. *Journal of Financial Economics*, 142(2), pp.641-673.

Li, Y., Johnson, E.J., Zaval, L. 2011. Local warming: Daily temperature change influences belief in global warming. *Psychological Science*, 22(4), pp.454-459.

Li, Y., Vertinsky, I. B., Li, J. 2014. National Distances, international experience, and venture capital investment performance. *Journal of Business Venturing*, 29 (4), pp. 471-489.

Lindsey, L. 2008. Blurring firm boundaries: The role of venture capital in strategic alliances. *The Journal of Finance*, 63(3), pp.1137-1168.

Liu, X., Yuan, X., Ge, X., Jin, Z. 2024. Adaptation and innovation: How does climate vulnerability shapes corporate green innovation in BRICS. *International Review of Financial Analysis,* 94, p.103272.

Liu, Y., Maula, M. 2021. Contextual status effects: The performance effects of host-country network status and regulatory institutions in cross-border venture capital. *Research Policy*, 50(5), p.104216.

Luong, H., Moshirian, F., Nguyen, L., Tian, X., Zhang, B. 2017. How Do Foreign Institutional Investors Enhance Firm Innovation? *Journal of Financial and Quantitative Analysis*, 52(4), pp. 1449-1490.

Ma, S. 2020. The Life Cycle of Corporate Venture Capital. *Review of Financial Studies*, 33(1), pp. 358-394.

Maddala, G. S. 1983. *Limited Dependent and Qualitative Variables in Econometrics*. Econometric Society Monographs No. 3. Cambridge, UK: Cambridge University Press.

Mäkelä, M.M., Maula, M.V. 2008. Attracting cross-border venture capital: the role of a local investor. *Entrepreneurship and Regional Development*, 20(3), pp.237-257.

Manigart, S., Wright, M. 2013. Reassessing the relationships between private equity investors and their portfolio companies. *Small Business Economic*, 40: 449–479.

Manso, G. 2011. Motivating Innovation. *The Journal of Finance*, 66(5), 1823-1860.

Mansouri, S., Momtaz, P.P. 2022. Financing sustainable entrepreneurship: ESG measurement, valuation, and performance. *Journal of Business Venturing*, 37(6), p.106258.

Martinsson, G., Sajtos, L., Strömberg, P., Thomann, C. 2024. The effect of carbon pricing on firm emissions: Evidence from the Swedish CO2 tax. *The Review of Financial Studies*, 37(6), pp.1848-1886.

McPherson, M., Smith-Lovin, L., Cook, J.M. 2001. Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 27(1), pp.415-444.

Meuleman, M., Jääskeläinen, M., Maula, M. V., Wright, M. 2017. Venturing into the unknown with strangers: Substitutes of relational embeddedness in cross-border partner selection in venture capital syndicats. *Journal of Business Venturing,* 32(2), pp. 131-144.

Meyer, J.E., Shao, J. 1995. International venture capital portfolio diversification and agency costs. *Multinational Business Review*, pp. 53–58.

Mizruchi, M.S., Stearns, L.B. 2001. Getting deals done: The use of social networks in bank decision-making. *American Sociological Review*, 66(5), pp.647-671.

Mulier, K., Samarin, I. 2021. Sector heterogeneity and dynamic effects of innovation subsidies: Evidence from Horizon. *Research Policy*, 50 (10), 104346.

Murray, G. 1995. Evolution and change: An analysis of the first decade of the UK venture capital industry. *Journal of Business Finance & Accounting*, 22(8), pp. 1077 – 1106.

Muzyka, D., S. Birley and B. Leleux 1996, Trade-offs in the Investment Decisions of European Venture Capitalists. *Journal of Business Venturing*, 11(4), pp.273-287.

Nahata, R. 2008. Venture capital reputation and investment performance. *Journal of Financial Economics,* 90 (2), pp. 127-151.

Nahata, R., Hazarika, S., and Tandon, K. 2015. Success in Global Venture Capital Investing: Do Institutional and Cultural Differences Matter? *Journal of Financial and Quantitative Analysis*, 49(4), pp. 1039-1070.

Nahata, R., Hazarika, S., Tandon, K. 2014. Success in Global Venture Capital Investing: Do Institutional and Cultural Differences Matter? *Journal of Financial and Quantitative Analysis*, 49(4), 1039-1070.

Nanda, R., Rhodes-Kropf, M. 2017. Financing risk and innovation. *Management science*, *63*(4), pp.901-918.

Nathan, M., Rosso, A. 2022. Innovative events: product launches, innovation and firm performance. *Research Policy*, 51(1), 104373.

Nguyen, G., Nguyen, M., Pham, A.V., Pham, M.D.M. 2023. Navigating investment decisions with social connectedness: Implications for venture capital. *Journal of Banking & Finance*, 155, p.106979.

Nguyen, J.H., Phan, H.V. 2020. Carbon risk and corporate capital structure. *Journal of Corporate Finance*, 64, p.101713.

Nitzan, I., Libai, B. 2011. Social effects on customer retention. *Journal of marketing*, *75*(6), pp.24-38.

Noy, I. 2009. The macroeconomic consequences of disasters. *Journal of Development Economics,* 88:221–31.

Ooghe, H., Manigart, S., Fassin, Y. 1991. Growth patterns of the European venture capital industry. *Journal of Business Venturing*, 6(6), pp. 381–404.

Ozkan, A., Temiz, H., Yildiz, Y. 2023. Climate risk, corporate social responsibility, and firm performance. *British Journal of Management*, 34(4), pp.1791-1810.

Pacheco, D.F., Dean, T.J., Payne, D.S. 2010. Escaping the green prison: Entrepreneurship and the creation of opportunities for sustainable development. *Journal of Business Venturing*, 25(5), pp.464-480.

Pankratz, N., Bauer, R., Derwall, J. 2023. Climate change, firm performance, and investor surprises. *Management Science*, 69(12), pp.7352-7398.

Pankratz, N.M., Schiller, C.M. 2024. Climate change and adaptation in global supply-chain networks. *The Review of Financial Studies*, 37(6), pp.1729-1777.

Papaioannou, E. 2009. What drives international financial flows? Politics, institutions and other determinants. *Journal of Development Economics*, 88(2), pp.269-281.

Pastor, Ľ., Stambaugh, R.F., Taylor, L.A. 2021. Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2), pp.550-571.

Patzelt, H., Shepherd, D.A. 2011. Recognizing opportunities for sustainable development. *Entrepreneurship Theory and Practice*, 35 (4), pp.631-652.

Peillex, J., El Ouadghiri, I., Gomes, M., Jaballah, J. 2021. Extreme heat and stock market activity. *Ecological Economics*, 179, p.106810.

Peng, L., Zhang, L. 2024. Unleashing the crowd: the effect of social networks in crowdfunding markets. *Management Science*.

Petersen, M.A., Rajan, R.G. 2002. Does distance still matter? The information revolution in small business lending. *The Journal of Finance*, 57(6), pp.2533-2570.

Petkova, A.P., Wadhwa, A., Yao, X., Jain, S. 2014. Reputation and decision making under ambiguity: A study of US venture capital firms' investments in the emerging clean energy sector. *Academy of Management Journal*, 57(2), pp.422-448.

Plagmann, C., Lutz, E. 2019. Beggars or choosers? Lead venture capitalists and the impact of reputation on syndicate partner selection in international settings. *Journal of Banking and Finance*, 100, pp. 359-378.

Poelhekke, S., Wache, B. 2026. When venture capital comes to town: Local ecosystem effects beyond funded ventures. *Journal of Business Venturing*, *41*(3), p.106588.

Popov, A., Roosenboom, P. 2012. Venture capital and patented innovation: evidence from Europe. *Economic Policy*, 27(71), pp. 447-482.

Porta, R.L., Lopez-de-Silanes, F., Shleifer, A., Vishny, R.W. 1998. Law and finance. *Journal of Political Economy*, 106(6), pp.1113-1155.

Porter M. 1992. Capital disadvantage: America's failing capital investment system. *Harvard Business Review*, 70, pp. 65-82.

Portes, R., Rey, H. 2005. The determinants of cross-border equity flows. *Journal of International Economics*, 65(2), pp. 269-296.

Poterba, J., French, K. 1991. Investor diversification and international equity markets. *American Economic Review*, 81, pp. 222–226.

Pursiainen, V. 2022. Cultural biases in equity analysis. *The Journal of Finance*, 77(1), pp.163-211.

Quas, A., Martí, J., Reverte, C. 2021. What money cannot buy: a new approach to measure venture capital ability to add non-financial resources. *Small Business Economics*, 57, pp.1361-1382.

Rao, S., Koirala, S., Thapa, C., Neupane, S. 2022. When rain matters! Investments and value relevance. *Journal of Corporate Finance*, 73, p.101827.

Rauch, J.E. 2001. Business and social networks in international trade. *Journal of Economic Literature*, 39(4), pp.1177-1203.

Rauch, J.E., Trindade, V. 2002. Ethnic Chinese networks in international trade. *Review of Economics and Statistics*, 84(1), pp.116-130.

Reagans, R. 2005. Preferences, identity, and competition: Predicting tie strength from demographic data. *Management Science*, 51, pp.1374–1383.

Rock, K. 1986. Why new issues are underpriced, *Journal of Financial Economics*, 15, pp. 187–212.

Rogers, E.M., Bhowmik, D.K. 1970. Homophily-heterophily: Relational concepts for communication research. *Public Opinion Quarterly*, 34(4), pp.523-538.

Sahlman, W. 1990. The structure and governance of venture capital organizations. *Journal of Financial Economics*, 27, pp. 473–521.

Sannajust, A., Groh, A. 2020. There's no need to be a pioneer in emerging private equity markets, *Journal of Corporate Finance*, 65, 101781.

Sapienza, H. 1992. When do venture capitalists add value? *Journal of Business Venturing*, 7, pp. 9–27.

Sapienza, H.J., Manigart, S., Vermeir, W. 1996. Venture capitalist governance and value added in four countries. *Journal of Business Venturing*, 11(6), pp.439-469.

Saunders, E.M. 1993. Stock prices and Wall Street weather. *The American Economic Review*, 83(5), pp.1337-1345.

Sautner, Z., Van Lent, L., Vilkov, G., Zhang, R. 2023. Pricing climate change exposure. *Management Science*, 69(12), pp.7540-7561.

Schaltegger, S., Wagner, M. 2011. Sustainable entrepreneurship and sustainability innovation: categories and interactions. *Business Strategy and the Environment*, 20 (4), pp.222-237.

Schertler, A., Tykvová, T. 2011. Venture capital and internationalization. *International Business Review*, 20(4), pp.423-439.

Seru, A. 2014. Firm boundaries matter: Evidence from conglomerates and R&D activity. *Journal of Financial Economics,* 111(2), pp. 381-405.

Shafi, K., Mohammadi, A. 2020. Too gloomy to invest: Weather-induced mood and crowdfunding. *Journal of Corporate Finance*, 65, p.101761.

Shepherd, D. A. 1999. Venture capitalists' assessment of new venture survival. *Management Science*, 45(5), pp. 624–634.

Shi, Y., Sorenson, O., Waguespack, D.M. 2024. The new argonauts: The international migration of venture-backed companies*, Strategic Management Journal*, 45(8), pp. 1485–1509.

Shin, M., Bae, J., Ozmel, U. 2025. Effect of venture capital investment horizon on new product development: Evidence from the medical device sector. *Journal of Business Venturing*, 40(1), p.106454.

Shive, S.A., Forster, M.M. 2020. Corporate governance and pollution externalities of public and private firms. *The Review of Financial Studies*, 33(3), pp.1296-1330.

Solow, R.M. 1957. Technical change and the aggregate production function. *Review of Economics and Statistics,* 39, pp. 312–320.

Sorensen, M. 2007. How smart is smart money? A two-sided matching model of venture capital. *The Journal of Finan*ce, 62, pp. 2725–2762.

Sorenson, O., Stuart, T. E. 2001. Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*, 106(6), 1546-1588.

Sorenson, O., Stuart, T.E. 2008. Bringing the context back in: Settings and the search for syndicate partners in venture capital investment networks. *Administrative Science Quarterly*, 53(2), pp.266-294.

Stein, J. C. 1989. Efficient Capital Markets, Inefficient Firms: A Model of Myopic Corporate Behavior. *The Quarterly Journal of Economics*, 104 (4), pp. 655-669.

Steinwender, C. 2018. Real Effects of Information Frictions: When the States and the Kingdom Became United. *American Economic Review*, 108 (3), pp.657–96.
S

troebel, J., Wurgler, J. 2021. What do you think about climate finance?. *Journal of Financial Economics,* 142(2), pp.487-498.

Strömberg, D. 2007. Natural disasters, economic development, and humanitarian aid. *Journal of Economic Perspectives* 21 3:199–222.

Sudek, R. 2006. Angel investment criteria. *Journal of Small Business Strategy*, *17*(2), pp.89-104.

Sunder, J., Sunder, S. V., Zhang, J. 2017. Pilot CEOs and corporate innovation, *Journal of Financial Economics,* 123(1), pp. 209-224.

Thomas Hellmann, T., Puri, M. 2002. Venture Capital and the Professionalization of Start-up Firms: Empirical Evidence. *The Journal of Finance*, 57(1), pp. 169-197.

Thompson, P. and Fox-Kean, M. 2005. Patent citations and the geography of knowledge spillovers: A reassessment. *American Economic Review*, 95(1), pp.450-460.

Tian, X. 2011. The causes and consequences of venture capital stage financing. *Journal of Financial Economics*, 101(1), pp. 132-159.

Tian, X. 2012. The Role of Venture Capital Syndication in Value Creation for Entrepreneurial Firms. *Review of Finance, 16*, pp. 245-283.

Tian, X., Wang, T. Y. 2014. Tolerance for failure and corporate innovation. *The Review of Financial Studies,* 27(1), 211–255.

Tversky, A., D. Kahneman. 1973. Availability: A heuristic for judging frequency and probability. *Cognitive Psychology* 5:207–32.

Uysal, V.B., Kedia, S., Panchapagesan, V. 2008. Geography and acquirer returns. *Journal of Financial Intermediatio*n, 17(2), pp.256-275.

Venturini, A. 2022. Climate change, risk factors and stock returns: A review of the literature. *International Review of Financial Analysis*, 79, p.101934.

Wang, D. J. 2020. When do return migrants become entrepreneurs? The role of global social networks and institutional distance. *Strategic Entrepreneurship Journal,* 14(2), pp. 125-148.

Weik, S., Achleitner, A.K., Braun, R. 2024. Venture capital and the international relocation of startups. *Research Policy*, 53(7), p.105031.

Wright, M., Pruthi, S., Lockett, A. 2005. International venture capital research: From cross-country comparisons to crossing borders. *International Journal of Management Review*, 7, pp. 135–165.

Wright, M., Robbie, K. 1998. Venture capital and private equity: A review and synthesis. *Journal of Business Finance and Accounting*, 25(5-6), pp. 521–570.

Wright, M., Thompson, S., Robbie, K. 1992. Venture capital and management-led, leveraged buy-outs: A European perspective. *Journal of Business Venturing*, 7(1), pp. 47-71.

Wu, S., Chun, K. H. 2019. Corporate innovation, likelihood to be acquired, and takeover premiums. *Journal of Banking and Finance*, 108, 105634.

Wu, Z., Salomon, R. 2017. Deconstructing the liability of foreignness: Regulatory enforcement actions against foreign banks. *Journal of International Business Studies*, 48, pp. 837–861.

Xie, F., Zhang, B., Zhang, W. 2022. Trust, incomplete contracting, and corporate innovation. *Management Science*, 68(5), pp.3419-3443.

Yan, S., Almandoz, J., Ferraro, F. 2021. The impact of logic (in) compatibility: Green investing, state policy, and corporate environmental performance. *Administrative Science Quarterly*, 66(4), pp.903-944.

Yan, Y., Li, J., Zhang, J. 2021. Protecting intellectual property in foreign subsidiaries: An internal network defense perspective. *Journal of International Business Studies*, 53, pp. 1924-1944.

Zaheer, S. 1995. Overcoming the liability of foreignness. *Academy of Management Journal*, 38 (2), pp. 341-363.

Zaheer, S., Mosakowski, E. 1997. The dynamics of the liability of foreignness: A global study of survival in financial services. *Strategic Management Journal*, 18(6), pp.439-463.

Zaval, L., Keenan, E.A., Johnson, E.J., Weber, E.U. 2014. How warm days increase belief in global warming. *Nature Climate Change*, 4(2), pp.143-147.

Zhang, P., Deschenes, O., Meng, K., Zhang, J. 2018. Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management*, 88, pp.1-17.

Zhang, S. 2024. Carbon returns across the globe. *The Journal of Finance*, 80(1), pp.615-645.

Zhang, Y. 2025. Corporate venture capital and firm scope. Journal of Financial and Quantitative Analysis, 60(1), pp.336-373.