ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
MSc Economics & Business
Master Specialisation Financial Economics

Governmental Venture Capital: Spurring Innovation?

A Panel Data Study on the Effect of Governmental Venture Capital Investments on Innovation in Europe

Author: W.R. van 't Spijker
Student number: 539032ws
Thesis supervisor: Dr. J.J.G. Lemmen
Second assessor: Y.S. Gangaram-Panday
Finish month: July 2020

Preface and Acknowledgements

During the Masters' thesis process, I have gained a vast amount of knowledge about the venture capital (VC) market, scientific research, and how to overcome obstacles that arise during the writing process. I am very grateful for the educational opportunities I have had over the past years. Furthermore, I am honoured to have written my thesis at the ESE. I would like to thank my family and friends for their encouragement over the past months and years. Lastly, I would like to especially thank Dr. J.J.G. Lemmen for his shared knowledge, guidance, and supervision during the thesis process, which proved to be of great value to me.

Yours sincerely,

W.R. van 't Spijker

Abstract

This study examines the effect of governmental venture capital (GVC) investments by using fixed effects models in the period 2008-2015. The study relies on pan-European data spanning several industries. Innovation is measured through patent filings and citation-weighted patents at the company level before and after the years of the investments. The findings indicate that GVC investments positively affect innovation compared to non-VC-backed companies. No evidence that GVC results in less innovation than private venture capital (PVC) and corporate venture capital (CVC) is found. Some evidence suggests that homogenous investments impact innovation less than heterogenous investments. This research serves as an important contribution to existing research regarding GVC and could serve as a foundation for further research on the impact of GVC investments on innovation in Europe.

Keywords: European **(**Governmental) Venture Capital, Innovation, Patents, Fixed Effects Models, Propensity score matching

JEL classification: C14, C23, G24, O31, O34

Table of Contents

List of Tables and Figures

1 Introduction

Venture capital (VC) was born in 1946 and finances recently created innovative companies (Bottazzi & Da Rin, 2002). Several previous studies have assessed VC to understand its dynamics and objectives. In essence, VC firms consist of funds that rely on capital raised from a variety of limited partners and subsequently invested in companies to achieve a profitable exit after a predetermined period. Venture capitalists (VCs) contribute in several ways to the development of innovative companies. First, VCs provide small and medium enterprises (SMEs) the financial resources to further develop their ideas and inventions. Second, VCs perform coaching and monitor activities. Third, VCs help SMEs to expand their business contacts and alliances (Cumming, Grilli, & Martinu, 2017).

Previous literature has thoroughly examined the impact of VC on innovation. The results across the literature are mixed. On the one hand, research suggests that VCs are 'cherry picking' innovative companies (Baum & Silverman, 2004; Engel & Keilbach, 2007). On the other hand, the previous research shows that inventiveness and innovativeness of companies is positively affected by VCs (Arqué-Castells, 2012; Bertoni, Croce, & D'Adda, 2010). Even though the performance and innovation of VC firms have been widely assessed in previous research, the existing studies mainly focus on private VCs (PVCs) or consider VC without further specifying the VC firm's investment objectives and governance structure.

Although the existing literature comprehensively examines VC firms and their relationship to innovation, it does not extensively distinguish between the impacts of different types of VC. Bertoni and Tykvovà (2015) were one of the first to investigate the relationship between governmental VC (GVC) and innovation. Brander, Egan and Hellmann (2008) examined the relation between GVC and innovation in a Canadian setting. However, they failed to draw precise conclusions, due to a lack of available data. The lack of existing research in the field of GVC is puzzling, as a survey conducted with over 1400 European investment firms indicated that 20% of the total raised capital in VC funds come directly from government-related entities in 2019 (Invest Europe, 2020). Moreover, Bertoni and Tykvovà (2015) report that taxes paid by citizens represent one of the largest sources of capital for VCs in Europe.

The European Union (EU) has introduced initiatives to pursue the integration of its VC market. The European Commission envisions VCs as an important catalyser of employment, innovation, and economic growth in Europe. Therefore, they founded the European Investment Fund (EIF) with the objective to provide funding to SMEs and ultimately create positive externalities by increasing employment and innovation across European regions (Kraemer-Eis, Signore, & Prencipe, 2018). In addition, national governments and other public authorities across Europe are involved in national VC markets to decrease financing constraints for entrepreneurial companies (which is referred to as the 'equity gap'), increase employment and spur innovation (Alperovych, Groh, & Quas, 2015; Bertoni & Tykvovà, 2015). Research has investigated the financial performance of GVC-backed companies. Previous literature has shown that, in general, GVC-backed companies financially underperform their

PVC-backed peers in terms of exit success (Alperovych et al., 2015; Cumming et al., 2017). This underperformance might be driven by the other than profit investment objectives of GVCs and the tendency of GVCs to invest more in economically lagging regions (Alperovych et al., 2015).

Therefore, this research aims to further analyse the impact of GVC investments. As GVC intends to create positive externalities in the form of increased employment and innovation, its success should not solely be measured by profits. Furthermore, the impact of GVC investments on innovation should be examined more thoroughly as little is known from the existing research on this subject. This brings me to the empirical research question examined by this paper: '*What is the effect of GVC investments on innovation in Europe?'*

This paper examines the impact of GVCs in several ways. Four hypotheses are formulated related to the impact of GVC investments on innovation. First, GVC investments are expected to positively impact levels of innovation in the years after the investment. Second, I hypothesize that GVC investments underperform PVC investments in terms of innovation. Third, I hypothesize that GVC investments do less well than CVC investments in terms of innovation. Lastly, I hypothesize that homogenous investments underperform heterogenous investments, as it is expected that combining governance and investment objectives of different VC types leads to more innovation.

To conduct the empirical analysis, I employ a novel panel dataset consisting of European VC investments from January 2008 to December 2015. To test the hypotheses, fixed effects regressions are used. The total number of patents filed by companies that received an investment is observed from five years before to five years after the investment. As VCs scout their targets before investing, examining the patenting activity in the five years leading up to the investment also proves relevant in the research. In addition, to decrease selection bias, the non-VC-backed control group is determined based on propensity score matching to examine the first hypothesis.

This paper contributes to existing research in several ways. First, in general, little research has been performed investigating the effect of GVC investments on innovation, despite their growing importance over the years. This research is one of the first to address an industry-agnostic and pan-European analysis on the effect of GVC investments on innovation, as 44 industries and 21 European countries are included in the sample. Second, to the best of my knowledge, this paper is the first to examine the differing impacts of investments of GVC versus CVC investments. Third, the transaction period of January 2008 to December 2015 allows the investigation of recent developments in the European VC market. The VC investments in this period have not yet been examined. This paper thus contributes to existing research by providing new insights on VCs funded by public authorities to spur innovation.

The main findings of this research reveal that, based on this sample, GVC investments positively impact innovation compared to companies that did not receive any VC investment. The results show that GVC investments do not significantly differ from PVC and CVC investments. Homogenous investments are likely to underperform heterogenous investments; however, these results become insignificant when using the citation-weighted innovation measure. Robustness tests indicate that other factors than the VC investments are likely to influence innovation as well. Therefore, this should be considered when interpreting the results.

The remainder of this paper is structured as follows: Chapter 2 presents the existing literature about VC and GVC. It describes how VC types differ, why GVC exists, and the effect of VC on innovation. Based on the previous literature, the hypotheses are then formulated. Chapter 3 discusses the data and methodology. Chapter 4 examines the results and robustness of the results, while Chapter 5 addresses the limitations of this research. The final chapter summarizes and concludes this paper.

2 Literature Review

This chapter discusses the existing literature on VC. It begins by describing the different types of VC. Second, the European VC market is examined and the role of GVCs is discussed. Last, the impact of VC investments on innovation and possible complications are reviewed.

2.1 Different types of VC

The activities of venture capital (VC) can be best described as searching and funding for innovative and promising companies (Bottazzi & Da Rin, 2002; Brander et al., 2008; Cumming et al., 2017). VC is present in various forms due to different types of ownership and governance structures (Da Rin, Hellmann, & Puri, 2013). The previous literature has distinguished between three forms of VC: private or independent VC (PVC), governmental VC (GVC), and corporate VC (CVC). The following paragraphs elaborate on the characteristics of PVC, GVC, and CVC, respectively. As all VCs possess different objectives, skills, and governance structures, it is important to discuss these characteristics before comparing them.

PVCs are organized as independent management companies that raise capital into a fund from several limited partners (Sahlman, 1990). Afterwards, the PVCs independently select target companies and attempt to obtain a high growth rate and profitable exit (selling their ownership stake) for their portfolio companies within an exit period of five to ten years (Gompers & Lerner, 1999).

In contrast, GVCs do not seek their funding with limited partners. Typically, their main investors and managing agencies are public authorities (Alperovych et al., 2015; Bertoni, Colombo, & Quas, 2015). Furthermore, GVCs aim to also increase employment and innovation rather than solely focus on obtaining a high financial return within the exit period (Gompers & Lerner., 1999). As GVCs pursue the objectives of governments and public authorities, they do not operate independently from their government officials. Since GVCs aim to increase employment and innovation, they tend to invest in economically less developed regions. Furthermore, they want to promote the network between research and industry (Bertoni & Tykvová, 2012). Within the existing literature, several definitions for the concept of GVCs exist. This varies from narrow definitions that classify VCs as governmental when they are managed by government related organizations to broader definitions that include national taxation policies to attract more private investors (Colombo, Cumming, & Vismara, 2016).

The last VC form considered in this paper is CVC. In general, CVCs operate as investment arms of large corporate parent companies. In other words, the main activity of the managing company differs from the VC investment arm (Chemmanur, Loutskina, & Tian, 2014). In this research, CVCs are considered to have either financial (e.g. Banks, Pension funds) or non-financial (e.g. multinationals) parent companies.

So far, the description of the different forms of VCs discuss their managing entities and investors. The next paragraphs elaborate on the variations in remuneration scheme and management incentives that might prove influential on the differences in success.

The variation in payoff schemes between PVC, CVC and GVC could prove a differentiator in the investment incentives (Cumming et al., 2017). Remunerations for GVCs are structured as fixed payment streams and thus not sensitive to the performance outcome, whereas PVCs' remuneration schemes rely on high profits and, therefore, the strong performance of the fund will benefit the firms' employees. Typically, the financial returns flow back to the general partners. In addition, in PVC firms it is not uncommon for employees to participate in the investments (Bertoni & Tykvovà, 2015; Cumming et al., 2017). Since the remuneration schemes for GVC firms are not related to the profits they earn, their employees are less motivated to obtain high profits (Cumming et al., 2017). In addition, Cumming et al. (2017) argue that these differences in compensation could increase agency problems and, ultimately, employee retention problems as PVCs can offer more generous wages than GVCs. Loosely speaking, these higher wages could serve as an incentive for talented employees to work for PVCs rather than for GVCs. Furthermore, CVCs often follow the remuneration policies of their corporate parents, which tend to be more fixed than those of PVCs (Chemmanur et al., 2014).

Furthermore, Leleux and Surlemont (2003) address the lack of independence of GVCs in the decision-making process. The decisions made by GVCs are political and focus on projects with higher societal benefits. In other words, GVCs may be forced to invest more in sustainable projects with a lower quality than PVCs. GVCs constantly balance the decisions between investing in the most promising companies from an investors' point of view on the one hand and creating positive externalities for society on the other hand (Leleux & Surlemont, 2003). Moreover, Cumming et al. (2017) argue that PVCs will always manage their portfolio companies in the most efficient way, even if this requires an alteration in management of the specific portfolio company, whereas GVCs are less likely to fire employees as their objective is to create employment. Ultimately this could cause a loss in economic efficiency. In addition, Cumming et al. (2017) describe that, in general, PVCs obtain lower cost bank loans than GVCs as the loan criteria of GVCs are usually set by the governments.

VCs do not solely invest on a stand-alone basis but also as syndicates. Syndication can be best described as the joint investments by different VC firms or funds in a company. Cumming et al. (2017) address multiple explanations for why syndicate investing adds value to both the company invested in and VCs. First, by investing in syndicate form more capital can be attracted and invested in the company. As a consequence, more capital can be invested in R&D and other sources to develop a company's performance. Furthermore, the screening process in advance of an investment becomes more accurate with the addition of multiple opinions. Ultimately, this reduces the likelihood of adverse selection. In addition, the syndication of different VCs augments the management skills, industry expertise and other non-financial benefits that could prove useful in improving the performance of companies (Cumming et al., 2017).

Differences in governance structures, remuneration schemes and investment objectives therefore ultimately lead to different outcomes regarding the success of investments. Considering the investment incentives of GVCs, Section 2.2 elaborates on the European VC market and its developments. It also discusses the objectives of GVC in more detail.

2.2 Developments in the European market and the role of GVC

Europe possesses one of the most developed VC markets in the world. However, relative to the VC market of the United States (US), a gap remains between European GDP growth and the development of its VC market (Bertoni et al., 2015). Bruton, Fried, and Manigart (2005) argue that the differences between the European and US VC market may be explained by the differences in economic and legal structures across Europe. To spur VC investments, a business-friendly legal environment is essential (Bertoni et al., 2015). In Europe, the supply of VC firms differs greatly across countries. The change over time in the total number of VC investments, as collected by the European Private Equity and Venture Capital Association (EVCA), indicate that more VC activity exists in Northwest than in Eastern Europe (European Commission, 2020). More specifically, countries as the United Kingdom, France and Germany demonstrate highly developed VC markets, whereas Eastern European countries exhibit fewer investments and lower market integration (Invest Europe, 2020). This difference has further increased since the 2008 financial crisis (Cumming et al., 2017).

The EU has implemented several initiatives to stimulate the VC market demand and supply side and reduce the disparity between regions (Cumming et al., 2017), like the establishment of the European Investment Fund (EIF) by the European Council in 1994. This fund aims to provide SMEs access to finance across Europe (Kraemer-Eis et al., 2018). However, market fragmentation across Europe remains high. Issues such as double taxation between countries systematically contribute to this fragmentation. Kraemer-Eis et al. (2018) therefore argue that there does not exist one integrated European VC market, but rather an 'aggregation of several markets' across European regions.

Consequently, national and cross-national GVCs have played a prominent role within the European market in the reduction of market fragmentation and other market failures (discussed in subsection 2.2.1.). In general, the European Commission argues that VC investments not only prove important on a company level but also for the greater European economy since SMEs improve productivity through innovation and represent a source of jobs (Bertoni et al., 2015; Kraemer-Eis et al., 2018). Market failures arising in the European VC market negatively influence the growth of these positive externalities (Cumming et al., 2017; Kraemer-Eis et al., 2018). Furthermore, market fragmentation and other failures not only affect the economy during an economic turmoil but could structurally harm the economy if consistently occurring (Kraemer-Eis et al., 2018). The next subsection further elaborates on the equity gap, which is viewed as a market failure as well as a rationale for the existence of GVC.

2.2.1 European VC market failures and rationale behind GVC

The 'equity gap' represents a market failure that is repeatedly mentioned in existing literature (Alperovych et al., 2015; Kraemer-Eis et al., 2018). The 'equity gap' arises when young and other innovative companies do not receive long-term financing from VC investors, which may occur for several reasons (Alperovych et al., 2015; Mason & Harrison, 1995).

First, even though seed and growth financing by VCs proves well-suited for aiding entrepreneurial companies in bringing their inventions and innovations to the market, SMEs may be at a very early stage of their lifecycle (Hellmann & Puri, 2000; Mason & Harrison, 1997), thus increasing the riskiness of the investment. In other words, the high fixed costs outweigh the potential financial return (Kraemer-Eis et al., 2018). Second, the region in which the company is located may also contribute to the 'equity gap'. In general, companies located in economically underdeveloped regions receive less financing (Alperovych et al., 2015). Third, the occurrence of asymmetric information between the investor and investee contributes to an increase in market failures (Colombo et al., 2016). Information asymmetry occurs when the investee possesses more information about the company than the investment company. In the case of VC, the entrepreneurial company has access to more information than the VCs. The degree of information asymmetry associated with SMEs is higher for young companies than older companies (Dixon, 1991). This difference may arise from the lack of collateral and proven track record of young innovative private companies. Moreover, the only assets they possess are the ideas of the entrepreneur. However, the entrepreneur has not yet proven his or her managerial skills (Kraemer-Eis, 2018). Along with the investment uncertainty, it could cause cooperation problems that affect the behaviour of investors, contributing to the company's difficulty in establishing investment terms and contracts. As a consequence, SMEs in Europe lack an adequate supply of financial capital (Colombo et al., 2016; Dixon, 1991; Kraemer-Eis et al., 2018).

Nonetheless, in theory, VCs exist to diminish this information asymmetry through their screening and monitoring of the quality of companies. However, the cost of due diligence may prove too high for VCs to invest, so that it is more cost effective to provide larger investments to later stage companies (Dixon, 1991; Kraemer-Eis et al., 2018). In recent years, the risk aversion among VCs and later stage investments has increased even further (Wilson, 2015). Kraemer-Eis et al. (2018) argue that economies of scale further diminish the relative chance of companies in an early stage of life of receiving funding. They mention that syndication (co-investments of different types of venture capital) is seen as a possible solution to overcome the information asymmetry problem.

The above-mentioned market failures contribute to the equity funding gap. When such failures occur, governments attempt to fix the problem. The launch of the Capital Markets Union (CMU) represents an example of a governmental initiative to further pursue European market integration (Kraemer-Eis et al., 2018). Public support can be motivated by the argument that the benefits of such an investment outweigh the total cost of company support. The existence of innovative SMEs is important for governments since they play a vital role in modern knowledge-based economies (Alperovych et al., 2015). In other words, the effects of the support will not only impact the invested company but also other companies as well as greater society. Entrepreneurial companies represent a source of jobs, innovation, productivity growth, and, importantly, a tool for disciplining established firms (Colombo et al., 2016). As SMEs are important for knowledge-based economies, in recent years, governments have become more active in the VC market to encourage the growth of such companies in Europe (Tykvovà, Borrel, & Kroencke, 2012).

All in all, the existence of GVCs in Europe is driven by the failures within the European VC market, due to fragmentation, risks that outweigh potential financial returns, and information asymmetry. The existence of entrepreneurial companies is important for the European economy for its productivity growth, source of jobs and innovation. However, these positive externalities are diminished by market failures. Government entities across Europe invest into SMEs and start-ups to decrease fragmentation and the equity funding gap. This should ultimately result in more employment and innovation. Subsection 2.3 touches upon the relationship between VCs and innovation, as this research mainly aims to determine if VCs succeed in spurring innovation.

2.3 The causality issue between VC investments and innovation

Previous research on the effectiveness of VC investments on the innovativeness of the companies has resulted in two contradictory sets of results. On the one hand, the literature has found evidence that VCs are well suited for spurring innovation. On the other hand, previous authors have claimed that it is not VC itself that produces an innovative company but rather factors that are not a direct result of VC investments The central concern here lies in the causal relationship between VC and innovation. This section discusses the findings of previous literature about causal relations of VC investments. It first discusses the first finding that VCs do spur innovation. It then describes the literature that claims the opposite. Finally, a table is presented to provide an overview of the previous findings.

2.3.1 VC investments do spur innovation

Kortum and Lerner (2000) represent one of the first studies to empirically test the impact of VC investments on innovation. Through an industry level analysis across 20 manufacturing industries in the US from 1965 to 1992, their findings support the hypothesis that VCs spur the patenting activity of companies. Along with the industry level analysis, they also conduct a company-level analysis. By analysing the VC-backed and non-VC-backed control group, their results suggest that VC-backed companies receive more as well as higher-quality patents than the non-VC-backed companies.

More studies have been conducted on VC investments on both the country and industry level. Samila and Sorenson (2010) analyse several metropolitan areas in the US. Through fixed effects and IV analyses, to control for the endogeneity that arises from VC investments, they conclude both that VC directly influences the number of patents received by a company and VC positively contributes to the supply of start-ups. The VC investment is more effective with a higher supply of capital funding. Popov and Roosenboom (2012) show similar results for European countries and industries.

In addition, more recent studies conduct company-level analyses on the impact of VC on innovation. In their paper, Bertoni et al. (2010) describe how the presence of VC can lead to higher R&D investments and ultimately boost the company’s innovation output. This positive impact occurs due to the expertise of the VCs in actively managing companies and protecting them from opportunistic behaviour by entrepreneurs inside the company. Furthermore, Bertoni et al. (2010) describe how VC investors fulfil an important coaching role that could ultimately increase total R&D investments and innovation output. This coaching mostly appears through establishing strategic goals and providing financial and human resources (Bertoni et al., 2010). However, VCs and entrepreneurs may also conflict, which could result in a negative relationship between VC and innovation and ultimately lead to lower innovation output. These disputes may arise due to differences in the strategies followed by VCs versus those of the entrepreneurs. The resulting disagreement could lower the likelihood that the entrepreneur participates and invests in innovative projects (Bertoni et al., 2010).

Bertoni et al. (2010) examine 33 VC-backed companies and 318 non-VC-backed companies in the new technology industry in Italy. They measured innovation through patent counts and arrived at two main findings. First, their results support the hypothesis that VCs positively affect the patenting activity. Second, they find that the VC-backed-companies did not demonstrate a higher patenting propensity before their funding by VCs.

Arqué-Castells (2012) finds that the patenting activity of companies increases after an VC investment. The increase is most present in the two years after the investment. After this period, it again decreases as VCs focus more on sales of the product after fully developing it rather than creating a new one. In short, patent applications follow an inverted U shape over time. Arqué-Castells (2012) states that this serves as indirect evidence that VCs do not fund basic research. To control for and compare the impact of VC investments, he included a large non-VC-backed control group in his analysis. VC-backed-companies demonstrate a higher patenting rate than the control group companies.

2.3.2 VC investments do not spur innovation

Several studies conducted on both the industry and company level contradict the possible causal relationship between VC investments and innovation growth. In their industry-level study, Ueda and Hirukawa (2011) state that policymakers solely interpret the relationship between VC and innovation growth as positive. However, this view fails to consider potential issues of reverse causality; for example, start-ups and SMEs that are innovative receive more funding from VCs than non-innovative companies. These start-ups and SMEs also self-select certain VCs. In this case, VCs are complements that further spur growth and innovation, rather creating it. Ueda and Hirukawa (2011) find that innovation is often positively related to future VC investment. Little evidence exists that supports the hypothesis that VC itself contributes to innovation (Ueda & Hirukawa, 2011).

Baum and Silverman (2004) distinguish VCs as either ‘scouts’ or ‘coaches’. Scouts are VCs that are able to identify companies with high potential, whereas the latter type of VCs aid in realizing the company’s goals. They find that the total funding amount is affected by the total applications and patents granted in the year prior to VC investment. They also observe that patenting activity is not impacted by the amount of VC funding. They perform a negative binomial regression on a pooled cross-section dataset with the patent counts as the dependent variable to estimate the number of total applications within a prespecified time interval (Baum & Silverman, 2004)

Engel and Keilbach (2007) conduct a company-level analysis on young German innovative companies. They match VC-backed-companies to those that did not receive VC funding based on their age, size, and industry affiliation. They find evidence that the VCs backed companies do indeed demonstrate a higher rate of patent applications than the non-VC-backed companies. However, the patent application rate is already higher before the VCs investment. Their evidence suggests that VCs choose companies based on their innovative output before their investment because the level of innovative output does not change after the VC investment occurs (Engel & Keilbach, 2007).

Caselli, Gatti and Perrini (2008) perform an empirical analysis of 37 Italian companies that are VC backed, examining the impact of the investment on innovation and growth compared to a control group of propensity-score-matched companies. They find that the funded companies demonstrate more innovation before funding. However, after funding occurs, innovation is no longer promoted; rather, the VCs direct their efforts towards improving the company's profitability and management (Caselli et al., 2008)

Table 1: Literature Overview of VC and Innovation

	VC spurs innovation		
	Research characteristics	**Methodology**	**Main finding(s)**
Country/ industry			
Kortum and Lerner (2000)	• US manufacturing industries 1965-1992	• Dependent variable patents issued • Industry level analysis across VC backed and non-VC-backed companies • OLS and IV regressions	• VCs impact innovation • Regions affect innovativeness • VC and R&D represent possible substitutes
Samila and Sorenson (2010)	• Industry-level analysis US 1993-2002	• Fixed effects and IV. • IV analysis is used to reduce the concerns of endogeneity of VC investments	• VCs directly influence the patents amount and supply of new start-ups
Popov and Roosenboom (2012)	• European industry level analysis 1991-2005 • 21 European countries and 10 manufacturing industries	• Dependent variable used are number of granted patents • OLS and IV regressions	• Mentions concerns about causality. However, for high-tech industries VC spurs innovation. • VCs foster innovation more in entrepreneurial countries
Company level			
Bertoni et al. (2010)	• Company-level analysis among high tech companies in Italy: 33 VC-backed and 318 control companies	• Random effects Poisson and Probit • Dependent variable: patent counts and patent dummy	• VC investments positively affect patenting • Before funding, it is not likely that VC-backed-companies patent more than other companies

	Research characteristics	Methodology	Main finding(s)
Arqué-Castells (2012)	• 505 VC-funded innovative companies in Spain 2003-2005 analysis is on company level	• Poisson and Probit models • Test variable is dummy that takes 1 in the year of entry	• Number of patent applications follow an inverted U shape over time
VC does not spur innovation			
	Research characteristics	**Methodology**	**Main finding(s)**
Country / industry			
Baum and Silverman (2004)	• 73 VC-backed biotech companies and control companies in Canada	• Several dependent variables to measure the performance of start-ups: patent count and amount of financing before IPO • Random effects and GLS	• The amount of financing does not influence the innovation output
Ueda and Hirukawa (2011)	• Industry level analysis in the US	• Innovation measures: patent counts and total factor productivity growth	• Innovative companies receive more funding from VCs • No evidence for growth of innovation after investment
Company level			
Engel and Keilbach (2007)	• Company level analysis based on 142 German start-ups 1995-1998	• Analysis focused on employment growth and innovation growth • Dependent variable: patent applications • Propensity score matching	• Companies with higher innovation are funded more often. The funded companies are not more innovative than the controls after investment
Caselli et al. (2008)	• Company level analysis based on matching procedures on 37 Italian VC-backed and non-VC-backed companies from 1995-2004	• Matching of VC-backed and non-VC-backed	• Being innovative is a requirement to receive VC funding • After funding there is no continued innovation growth

2.4 The impact of GVC and CVC on innovation

Subsection 2.3 discussed the literature examining the impact of VCs on innovation in their general form. This subsection reviews the previous literature on the influence of GVCs and CVCs on innovation.

2.4.1 The relation of GVC to innovation output

Little is known about the relationship between GVCs and innovation. The results on this research question are mixed and thus inconclusive (Bertoni & Tykvovà, 2015; Brander et al., 2015). Colombo et al. (2016) and Kraemer-Eis et al. (2018) argue that the way GVCs are involved in the investment could be of importance in their capability to spur innovation. Colombo et al. (2016) claim that GVC investments lead to slightly better results when they invest alongside an PVC through a syndicate. These papers further highlight that creating a government-supported fund of funds would produce more favourable results than direct investments. Wilson (2015) finds that a recent development in OECD countries is the indirect investment by GVCs, by co-investing alongside PVCs or through fund-of-funds, for example. In addition, Brander et al. (2015) observe that companies funded through PVC-GVC syndicates receive on average more subsequent PVC funding than homogenous PVC or GVC investments.

Existing research on the impact of GVCs on innovation capability is not widely available for Europe. However, some attempts have been made to measure the impact of GVC on innovation and its relative impact compared to other forms of VC. On the one hand, Jääskeläinen, Maula, and Mullen (2007) argue that PVCs possess governance structures and pursue investment strategies that seek, in particular, high profits. This behaviour may result in higher innovation than when GVCs invest. On the other hand, Gompers (1996) states that PVCs possess a short-term investment horizon. This could result in lower R&D spending and thus lower innovation (Lerner, 2002).

Existing literature provides mixed results on the impact of innovation and the heterogeneity of VCs. By measuring the Canadian patenting output through probit and negative binomial regressions that include fixed effects for year and industries, Brander et al. (2008) attempts to measure the impact of different types of VC. Due to a severe lack of data, they fail to achieve strong results. However, they also argue that the results do not justify the low financial performance of GVC investments. Such a performance could be justified if the GVCs succeeded in increasing employment and innovation.

Bertoni and Tykvovà (2015) attempt to measure the impact of GVC and PVC investments on innovation using fixed effects in a panel data setting by analysing the innovation in young European biotechnology companies. They reveal a nuanced view on the ability of GVC to spur innovation within the invested companies, observing that homogenous GVC investments do not impact innovation more than the non-VC-backed control group. In addition, when comparing GVC and PVC investments, they conclude that PVC-backed companies are more innovative than GVC-backed companies. Together, these findings suggest that GVC represents a poor substitute for PVC. However, they argue that GVC is a good complement for PVC investments when examining mixed syndicate investments, as the rate of patent stock growth in syndicate investments outperforms that in homogenous investments (Bertoni & Tykvovà, 2015). They propose two possible explanations why mixed syndicates outperform homogenous PVC investments: the difference in management type of the companies and the combination of different types of knowledge, either of which could result in higher innovation. More specifically, homogenous GVC investments probably lack the ability to encourage the management to improve the performance in terms of profits and innovation. However, a syndicate between PVC and GVC will probably result in both encouragement for short-term profits and a long-term commitment. This can increase the level of inventions (Bertoni & Tykvovà, 2015).

2.4.2 CVC and innovation

Chemmanur et al. (2014) investigate the difference in innovation performance between CVCs and PVCs. They state that differences in the organizational structure contributes to the different set of investment goals. First, CVCs demonstrate longer investment horizons than PVCs. CVCs invest on behalf of their corporate parents and thus possess an infinite lifespan, whereas PVCs are subject to a lifespan of at most 10 years. Second, CVCs pursue more strategic goals aside from solely high financial returns, unlike PVCs. Third, the parent company might operate in the same sector as the investee, providing CVCs with industry knowledge superior to PVCs. Chemmanur et al. (2014) argue that these three differences allow CVCs to be more effective in spurring innovation. However, CVC-backed-companies are less profitable than PVC companies. In general, CVCs often invest alongside other VC firms (Dushnitsky, 2006). The results presented by Chemmanur et al. (2014) suggest that a significant treatment effect exists of CVCs on the innovation performance of a company. Their analysis unravels the two mechanisms most likely to contribute to the ability of CVCs to spur innovation better than PVC. First, a better technological fit between the CVCs and the companies exists. Second, CVCs demonstrate a relatively greater tolerance of failure than PVCs do.

However, some scientists argue that the organization of CVCs might adversely impact innovation growth. As previously mentioned, CVCs represent operating subsidiaries of corporates. Consequently, CVCs must report the amount they invest into innovation to the corporate parent company. This might adversely influence the innovation of portfolio companies when the corporate programs are restrictive (Chemmanur et al,. 2014; Rajan, Servaes, & Zingales, 2000; Seru, 2014). Furthermore, CVCs commit to the strategic goals of their parents. This commitment incentivizes them to employ those resources and knowledge for the objectives of the parent company rather than stimulating innovation solely within the company they invest in. Lastly, the compensation structure differs between the two types of VCs. As previously described, PVCs possess performance-based remuneration schemes, whereas CVC compensation is often tied to the fixed salary and bonus policies of the corporate parent company. The investment goals of CVCs are related to the corporate parent company (Chemmanur et al., 2014).

2.5 Formulation of Hypotheses

To answer the general research question, '*What is the effect of GVC investments on innovation in Europe?*' I formulate different hypotheses on the impact of VC investments, particularly GVC investments. To develop the hypotheses, I rely on the previously discussed findings and theoretical frameworks from the literature. This subsection briefly elaborates on the formulation and economic rationale of the hypotheses.

This paper focuses on GVCs, which have an implicit or explicit objective to increase the innovation of the company to whom they provide funding (Bertoni & Tykvovà, 2015). The reasons why GVCs exist are extensively discussed in the literature review (e.g., market fragmentation, positive externalities, and market failures). However, GVCs may also be interested in sustaining high innovation in a company for the following reasons. First, because knowledge spill overs and innovation provide value for society beyond just the value provided to the innovative companies in question—in other words, positive externalities are produced (Griliches, 1992). Second, knowledge spill overs prove important for the development of the geographical area the company is situated in (Bertoni & Tykvovà, 2015). To this extent, GVCs could support innovation since this aids in the development of the national or regional economy.

Bertoni and Tykvovà (2015) observe that the investment process of GVCs and other VCs does not differ too much; both enter by obtaining an equity stake in the company, support its development, and ultimately exit it by selling the equity stake. Nonetheless, the previous research reports mixed results on the relationship between GVC and innovation. Bertoni and Tykvovà (2015) provide evidence that

GVC investments do not result in significantly higher innovation. However, the relationship between GVC investments and innovation is not widely examined, therefore the impact remains ambiguous.

The first hypothesis examines the impact of GVC investments on innovation compared to companies that did not receive GVC funding. I expect, relying on the objectives of GVC investments, that GVCs pursue innovation and succeed in this objective. Therefore, the following hypothesis is formulated:

Hypothesis 1: GVC investments positively impact innovation

In addition, the possible difference between GVC and PVC investments is important to consider because the VC firms differ in objectives, investment horizons, management fees, and incentives. Previous literature could not arrive at universal conclusions. On the one hand, GVCs are more incentivized to increase innovation than PVCs are. On the other hand, PVCs possess more motivation to deliver better results than GVCs. Moreover, the results presented by Bertoni & Tykvovà (2015) indicate that the PVCs impact innovation more than GVCs do. Furthermore, PVCs can 'cherry pick' promising companies to invest in, where GVCs also invest in relatively economically underdeveloped regions because they have more responsibility to society and seek to generate positive externalities (Alperovych et al., 2015). Considering the specific components affecting the investment objective and ultimately their relationship to the innovation output of the company, the following hypothesis is:

Hypothesis 2: GVC investments impact innovation less than PVC investments

Chemmanur et al. (2014) find that CVC impacts innovation more than PVC does. To the best of my knowledge, the relationship between GVC and CVC has not been examined in previous research. Therefore, the relationship is ambiguous. However, based on the literature, I hypothesize the following:

Hypothesis 3: GVC investments impact innovation less than CVC investments

The final hypothesis relies on the complementary strength of VCs (PVC, GVC and CVC) in spurring innovation in the post-investment period. As discussed in the literature review, syndication and thus combining resources, different management structures and different investment goals by the VC types should increase the capability of the companies to obtain higher innovation after investment. Therefore, the final hypothesis is as follows:

Hypothesis 4: Homogenous investments impact innovation less than mixed syndicate (heterogenous) investments [1]

[1] Homogenous investments are investments made on a stand-alone basis or investments with multiple venture capitalists from the same type (PVC, CVC or GVC)

3 Data and methodology

To examine the main research question, an empirical setup is used. This chapter discusses the dataset composition and methodology. First, it describes the variable that serves as a proxy for innovation. Second, it examines the data collection of the VC investments. Third, the control variables are briefly discussed. The composition of the non-VC-backed control group and the final sample is then explained. Finally, the empirical models to test the hypotheses are presented.

3.1 Innovation measures

R&D expenditures or announcements of new products may both serve as measurements of innovation. R&D expenditures and the number of patents are positively related. The internal capabilities to perform research could be argued as essential in generating outputs that need to be patented (Artz, Norman, Hatfield, & Cardinal, 2010). R&D expenditures represent a proxy for the annual capital investment that contributes to the 'stock of knowledge' (Hall, Griliches, & Hausman,1986). In addition, new product announcements have been cited as a potential proxy for the innovativeness of a company (Hagedoorn & Cloodt, 2003). However, the relevant data is usually only available at the industry, rather than company, level. Furthermore, one of the major problems with this method is the reliance of such data on press releases of the marketing departments of companies. This implies a lack of quality screening of the new product since its quality is solely examined by the companies themselves (Hagedoorn & Cloodt, 2003).

Another method to measure innovation is by counting raw patents. A patent is best described as a legally approved document that assigns the exclusive right to use a product, service, or process for a predetermined time horizon (Griliches, 1998). Katila (2000) justifies the use of patents as an innovation measure because they measure the output of new ideas and inventions. Furthermore, he argues that patents represent an indicator of technological change at an early stage of development. This argument further underlines the importance of patents as indicator for innovativeness. Hagedoorn and Cloodt (2003) observe that patent counts and citations are often employed to measure the inventiveness of a company. Both the patents possessed or patent applications by the company could be analysed, even if applications are not granted yet. Patents measure innovative performance by determining the rate of introduction of new products introduced to the market (Hagedoorn & Cloodt, 2003).

The use of patents as a measure for innovation is also criticized since patents are primarily legal documents that protect the invention from being copied (companies apply for a patent to protect their intellectual property). However, Mansfield (1986) states that strategies other than patenting, such as secrecy, in the case of rapid innovation might also be used. Engel and Keilbach (2007) mentions three reasons why patents may not account for all innovation output. First, not all innovations can be patented. Second, if innovations are patentable, a company might not apply for a patent since the innovation cycle is shorter than the duration of patenting. Third, companies can decide not to apply for a patent because the company must disclose some knowledge about the innovation which is then accessible for competitors (Engel & Keilbach, 2007). Furthermore, patenting may not be valuable in cases where the invention is too costly to duplicate for competitors. Therefore, companies could decide not to patent (Mansfield, 1986).

A significant share of the research examining the impact of VC on innovation uses patents as a proxy for innovation (Bertoni & Tykvovà, 2015; Popov & Roosenboom, 2012). However, some authors argue that patents themselves do not per se indicate innovation but rather invention, which is not necessarily valuable. To correct for this problem, researchers should also consider 'quality' patents, measuring quality by forward citations and patent originality, for example (Brander et al., 2008).

Arqué-Castells (2012) presents two additional considerations for the use of patents as a proxy for innovation. First, he contends that the typical time delay between the application date and grant date should be considered; typically, the delay between filing a patent to the granting date lasts several years. Arqué-Castells (2012) argues that to accurately proxy the time of inventions, one should focus on patent applications, as often patents are already published within two years after the invention. Second, patents are imperfect as not all inventions are patented. However, in the absence of R&D expenditures and innovation surveys, patent applications can be considered the best proxy (Arqué-Castells, 2012). However, one can argue that using applications not yet granted does not sort patents for quality. Backes-On this point, Gellner and Werner (2007) observe that patent applications represent a way to signal the quality of the company. Since filing a patent cannot occur without effort, a patent application is thus already a signal of the innovativeness of a company.

To measure the degree of innovation pursued by VC firms, Brander et al. (2008) compare the patent portfolios of firms financed by GVC with those financed by PVCs. They argue that patents do not represent a perfect measure of innovation. However, this measure is assumed to be a reliable and good proxy. In addition, it is commonly used. Brander et al. (2008) contend that it is therefore reasonable to start with patents as a proxy when measuring the effect of venture capital on innovation. However, Brander et al. (2008) argue that future research should enhance this method with other measures of innovation, such as R&D expenditures and differences between high and low technology companies. Brander et al. (2008) average the citations and patent originality on a company basis to measure innovativeness.

3.2 Data collection

The VC investments are extracted from ThomsonOne (T1) database (formerly known as VentureXpert). In the existing literature, this is the most common publicly available database to use in VC analyse (Popov & Roosenboom, 2012; Brander et al., 2015). ThomsonOne provides thorough coverage for European deals made after 2000. Through ThomsonOne, I identified 5767 unique companies in Europe that received one or more funding rounds from January 1, 2008 to December 31, 2015.

The investment rounds included are either seed, early stage, expansion, or later stage investments (Popov & Roosenboom, 2012). Seed stage investments are broadly defined as providing small amounts of capital to entrepreneurs to determine whether their idea or invention is solid enough to potentially enter the market. The early stage investments are start-up investments or investments in companies that have already developed prototypes of their product. A company in the expansion stage already has products well introduced to the market. Such companies are attempting to acquire more capital and becoming profitable. The later stage comprises investments focus on helping the company to become the market leader and grow their sales potential (Bottazzi & Da Rin, 2002; Hellmann & & Puri, 2000; Sahlman,1990).

In total, I collected 7796 different investments after excluding unknown investment firms. This indicates that companies received multiple rounds of funding during the sample period. The unknown investment firms are excluded since they cannot be identified as either PVC, GVC or CVC.

In this research, I focus on small and medium enterprises in Europe. Therefore, I included those incorporated after 1990 from all European countries. Subsequently, the ThomsonOne companies were matched with the Orbis database using the batch search option to identify their BvD number. This was essential for obtaining the patent data. The patent data is collected from the Orbis Intellectual Property (IP) database. This database provides extensive coverage with information on 115 million unique patents worldwide.

I obtained patents based on their application date. In general, the process from filing a patent to the eventual granting could take several years (up to 10 years), because of the necessity of signing legal papers and the lack of fast response by the patent offices. Therefore, VC transactions after 2015 are not considered and patent applications are used as proxy for innovativeness. This method allows companies several years to file for patents after the investment. Due to the recency of the observation, patents filed later than 2015 are less likely to be granted and therefore patents that are not yet granted are included as well. Patent applications that are included are granted and pending patents, while withdrawn patents are not included in the database. The main reasons to choose patent applications rather than patents possessed by the company are twofold. First, patents based on application date better represent the timing of the specific innovation whereas existing patents possessed could be non-informative regarding the VCs impact on innovation. Second, the databases available for this study do not provide the data required to study patent stock. I extracted all patents from January 1, 2003 until May 1, 2020, filed at the European Patent Office (EPO) and World Intellectual Property Organization (WIPO). This means that the patenting activity of a company is observed in a 10-year period around the deal.

Only patents filed at the EPO and WIPO are included. Patent offices around the world in less developed countries could create bias because the quality of patent screening and legislation of filing a patent could differ across countries. In the extraction of data, total forward citations per patent are included as well. Forward citations are all citations from other patent filings a patent received from the date it was filed ensuing the patents are matched to the companies based on their BvD number. In the master dataset, only companies that filed for at least one patent in the 10-year period around the VC investment are included. This reduces the dataset to 2507 unique VC investments.

3.2.1 Identification of investor type

Existing literature addresses the lack of proper identification of ThomsonOne of all VC firm and fund types (Brander et al., 2015). Therefore, I manually crosschecked the investor firm and fund with Crunchbase, Orbis and the investment firm websites. This check was essential to accurately classify the firms as either PVCs, GVCs or CVCs.

No universal definition for GVC exists in the current literature (Colombo et al., 2016). The broader definitions consider private-government funds, direct government funds and fund of funds as governmental (Colombo et al., 2016). Alperovych et al. (2015) also identify universities and other public research authorities as GVCs. GVCs are identified based on their shareholders, investors, and the management of the investment firm. If this was a governmental or public authority, the firm is labelled as governmental. Moreover, universities were also classified as governmental. Examples of GVCs included in this definition are the High-Tech Gründerfonds, IP Group PLC, Development Bank of Wales Public Ltd, Brabantse Ontwikkelings Maatschappij NV, Leeds University, and VAEKSTFONDEN. A complete list of GVCs included in this sample can be found in Table A.1.

CVCs in this research are VCs that are controlled by corporations or institutional companies, such as pension funds, insurance companies, banks, other non-financials, and multinationals. Some examples of CVCs are Novo holdings, Swisscom AG, Robert Bosch VC GmbH, and BNP Paribas Capital Partners.

Additionally, to identify investments as either homogenous or syndicate investments, the investment date from ThomsonOne was used, meaning that if multiple VCs performed an investment on the same day, this was considered as a syndicate. If the investment constituted of one or more VCs of the same type the investment is classified as homogenous (PVC, CVC or GVC). If different forms of VC participated in the investment, the deal is considered as heterogenous (PVC-GVC, PVC-CVC, CVC-GVC and PVC-GVC-CVC)

3.3 Control variables

Several databases have been accessed to provide the company control variables (Orbis, Crunchbase, dealroom.co and Preqin). However, a lack of company data remains. Previous research faced similar problems (Bertoni & Tykvovà, 2015; Brander et al., 2008).

Nonetheless, I managed to incorporate two specific control variables that are considered in this field of research. Brander et al. (2008) include the number of VCs investing in each company as control variable. A similar control variable is the number of co-investors participating in the investment. Bertoni and Tykvovà (2015) included the logarithmic transformation of this variable in their fixed effect panel data analysis on the impact of GVCs on innovation. Park and LiPuma (2020) include the number of investors as a control variable. The rationale of controlling for the number of co-investors is to determine if investments with more firms participating ultimately leads to more innovation. Bertoni and Tykvovà (2015) report a positive significant effect of syndicate size on the innovation output.

The second control variable included in this research is company age. Previous research on that the relationship between GVC and innovation has shown that these variables have significantly positively impact the innovation output (Bertoni & Tykvovà, 2012; Bertoni & Tykvovà, 2015). Age measures the impact of maturity on the level of patenting and could also serve as an alternative proxy for company size as older SMEs are likely to patent more than young start-ups.

3.4 Computation of control group: propensity score matching

This research intends to measure the impact of VC investments on innovation of companies by addressing the causal link between innovation and VC investments. To measure this link, I included a control group in the univariate analysis using data gathered from Orbis and Orbis IP. The initial dataset of control companies was selected based on several criteria. First, the companies had to be active in Europe. Second, they should not have received any VC investment. Third, they should at least have filed for one patent at the WIPO or EPO between 2007 and 2017. Lastly, companies should not be older than 20 years old. Following these search criteria, I obtained a total of 12,097 different companies that represented appropriate potential control companies. However, this group could still suffer from selection bias regarding industries and countries. To decrease this bias, I applied the propensity score matching technique. The results are shown in the Tables A.2 and A.3.

The propensity score method is developed by Rosenbaum and Rubin (1983). By applying this method, each company receives a propensity score varying between 0 and 1. The higher the score, the higher the propensity of getting VC funding. The scores are estimated by probit regressions of the VC investment companies and control companies based on several characteristics. This method is widely accepted in the existing literature as will be described in the following paragraphs.

Engel and Keilbach (2007) match VC-backed companies to non-VC-backed companies. By matching those companies based on several characteristics, they reduce selection bias. Furthermore, they use the statistical results to draw conclusions regarding the causal relationship between VC and innovation. The evidence found by Engel and Keilbach (2007) suggests that VCs choose companies based on patent application rates before investment, because the innovative output does not increase after the investment occurs.

Bertoni and Tykvovà (2012) rely on propensity scores as well to obtain a control group that they could use for the regression analyses. They first divide the sample in two subsamples: VC-backed companies (treated) and non-VC backed companies (control). Afterwards, they match the companies based on the closest matching propensity score. They find that the best targets are small and young companies that already possess a significant number of patents. To check its robustness, they adjust the model for both PVC and GVC. The results remain similar for both types of VC; that is, PVCs and GVCs have the same selection criteria. However, GVCs seem to invest more rapidly and are less interested in patents.

Chemmanur et al. (2014) base their propensity score matching method on the three nearest neighbours on CVC and PVC investments. Grilli and Martinu (2014) used country, industry identification, age, and an indicator of company size to match VC-backed companies and non-VC-backed companies based on propensity scores.

Including a control group allows the comparison of GVC investments not only to other types of VCs but also to companies that did not receive any VC funding at all but could have received it based on their propensity score. As previously discussed, providing an analysis on non-VC-backed group is a common practice in VC literature as the causal relationship between VC and innovation is ambiguous.

3.4.1 The matching procedure

This subsection describes the matching procedure and the results of the balancing test, which are shown in Tables A.2 and A.3, respectively. The following matching criteria were considered in the procedure: country region, industry, age, and an indicator of company size. First, NUTS level codes are used to identify the control companies that operate in the same region as the VC-backed company, due to the argument that companies with similar activities are concentrated in certain areas and would attract similar VCs. Second, two-digit Standard Industrial Classification (SIC) codes are used to identify the company's industry. Two-digit SIC codes are used rather than three- or four-digit, as the latter could be too specific for the early-stage VC companies (Chemmanur et al., 2014). Third, age is included in the probit model to match companies based on their maturity and operating cycle. Lastly, to control for company size, a categorical variable that measures the company size is included. Ideally, assets would be used. However, in this research data on assets was unavailable as companies are private. To control for this effect, a proxy from Orbis that identifies a company as small, medium-sized, large, or very large is obtained. In this research, the three companies with the propensity scores closest to a VC-backed company are included as control company (Chemmanur et al., 2014).

In Table 2, the summary results of the balancing test are presented. 'Before matching' represents the results from the matching procedure as extensively reported in table A.2. The after matching joint significance of the covariates is $p > 0.999$, indicating a lack of significant differences between VC-backed and non-VC-backed group (Chemmanur et al., 2014). Overall, the mean bias is reduced from 9.5% to 1.5%. Graphs A.1 and A.2 visualize the sample composition based on propensity scores before and after the matching. Moreover, Graph A.2 shows more overlap between the VC-backed and non-VC-backed group than Graph A.1, which reduces the selection bias. The *p*-values for each independent variable of the probit regressions are insignificant, indicating the success of the matching procedure. Because the observed characteristics of the VC-backed and non-VC-backed distribution do not significantly differ, the null hypothesis that the VC-backed and non-VC-backed group are equal is not rejected.

All in all, the results show no need for concern about the effectiveness of the matching procedure as most of the *p*-values are insignificant and the bias is reduced to 1.5%. In total, 3041 control companies that did not receive funding and filed for at least one patent between 2007 and 2017 are included in the final sample.

Table 2: Results Balancing Test

This table presents the results of the matching procedure probit regressions. The first row presents the results before matching (full analysis reported in Table A.2) and the second row after matching (Table A.3). The dependent variable is equal to 1 if a company received funding and 0 if not. LR Chi2 are joint significant tests of covariates included in the matching procedure before and after matching. The mean and median bias represents the magnitude of the difference in the VC-backed group and the non-VC-backed companies based on the matching procedure.

Sample	Pseudo R2	LR Chi2	p>chi2	Mean Bias	Median Bias
Before matching	0.310	4155.810	0.000	9.5	6.3
After matching	0.009	62.530	0.999	1.5	1.1

3.5 Final sample decomposition

This subsection discusses the characteristics of the final dataset. In total, 21 European countries are included in the final sample. 3041 total non-VC-backed companies are included; as described, this group will serve as control group to measure the impact of VC investments on innovation growth. In total, 2507 VC investments are observed. Since the deal period is 2008-2015, companies may receive multiple funding rounds during this period in different years. All 2507 investments and 3041 control companies are observed for a 10-year period to measure their levels of innovation. The location sample distribution is roughly what one would expect, as many VC investments are concentrated in the United Kingdom, Germany, and France. This VC sample is representative of the findings of the survey from the EVCA and Eurostat database regarding VC investment in Europe (European Commission, 2020). Table 3 shows the number of VC investments across the different countries.

Table A.4 shows the distribution among the different industries. The table illustrates the sample distribution in broad industry classifications, as this research aims to analyse all types of industries. Based on the two-digit SIC codes, 44 industries are included in the final sample. However, since the innovation is measured based on patenting output in this research and only companies that filed for at least one patent are included, most of the companies included are active in manufacturing and services. Figure 1 shows the VC investment distribution of the sample per year, with the majority of VC investments occurring in the first year of the sample. Again, this distribution is in line with the trends indicated by the EVCA survey (European Commission, 2020).

Table 3: Investment Distribution across Countries
This table represents the distribution of the number of included VC investments across the European countries in 2008-2015.

Country	Number of VC investments	Percentage in sample
Austria	47	1.87%
Belgium	77	3.07%
Denmark	139	5.54%
Estonia	1	0.04%
Finland	120	4.79%
France	415	16.55%
Germany	518	20.66%
Hungary	3	0.12%
Iceland	5	0.20%
Ireland	68	2.71%
Italy	37	1.48%
Lithuania	2	0.08%
Luxembourg	1	0.04%
Netherlands	71	2.83%
Norway	72	2.87%
Poland	1	0.04%
Portugal	10	0.40%
Slovenia	2	0.08%
Spain	78	3.11%
Sweden	171	6.82%
United Kingdom	669	26.69%
Total	**2507**	100.00%

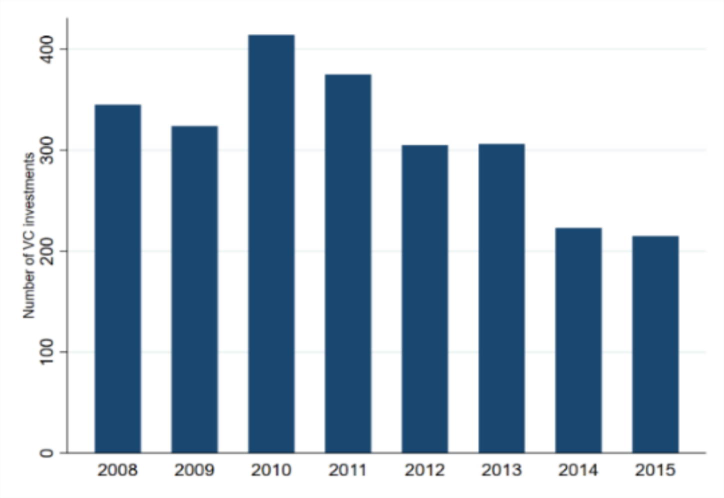

Figure 1: VC Investments 2008-2015
This figure represents all VC investments included in the final sample: 2507 unique investments.

Table 4 shows the distribution of VC investments by VC type. In the analyses, the investment types are defined as follows: PVC, GVC and CVC are homogenous investments, indicating this investment represents the stand-alone investment of one VC firm or multiple VC firms of the same investor type (Bertoni & Tykvovà, 2015). Heterogenous investments are defined as different types of VCs that invest together. The following heterogenous (syndicate) investments are defined in this research: PVC-GVC, PVC-CVC, GVC-CVC, and PVC-GVC-CVC. In this sample, investments possess a minimum of one investor; the largest investment consisted of eight VCs.

Table 4: Number of Investments per VC Type

This table presents the total number of investments included by VC type.

Investment type	**Number of investments**	**Percentage**
PVC	1132	45.16%
GVC	354	14.12%
CVC	271	10.81%
PVC-GVC	343	13.68%
PVC-CVC	240	9.57%
GVC-CVC	77	3.07%
PVC-GVC-CVC	90	3.59%
Total	**2507**	**100%**

3.6 Descriptive statistics and empirical model

The previous subsections elaborated on the data collection, propensity score matching of the non-VC-backed group, and characteristics of the investments in the sample. This subsection discusses the final dataset and empirical models employed.

As discussed in subsections 3.1 and 3.2, patent applications are used as a proxy for innovation. To measure the patenting behaviour around the investment period, a longitudinal dataset is computed. Longitudinal datasets allow the measurement of change over time, which permits the examination of the impact of VC investments on innovation. The observation period begins five years prior to the investment and ends five years afterwards to measure the increase in total patents. To measure the innovation of a company in a certain year, the natural logarithm of the number of total filed patents plus one is taken. The one is added to prevent the loss of observational years if the sum of all filed patents up to that year is zero. Using logarithmic transformation is common in this field of research to reduce skewness and kurtosis. By transforming the variables, outliers are less pronounced in the distribution. Consequently, the variables follow a more normal distribution. However, the data does not become totally symmetric (Bertoni & Tykvovà, 2015; Chemmanur et al., 2014). As VCs invest in start-ups and SMEs, not all companies are observed from the start of the observation period, as not all were incorporated yet.

As previously mentioned, to control for the quality of patents, previous research also relied on forward citations (Bertoni & Tykvovà, 2015; Chemmanur et al., 2014). Patents itself serve as a proxy for innovation. However, one could argue that just filing a significant number of patents does not indicate the quality and economic value or innovativeness of the patents, which may mean the company is less innovative than the number of patents would suggest. Therefore, this analysis also includes a citation-weighted measure to indicate the innovation of a company. Weighting the total patents by the forward citations allows the creation of a quality-weighted innovation measure. The number of citations over patents is computed annually and the natural logarithm is taken after the addition of a one. In this case, no observational years are lost.

Table 5 presents the descriptive statistics of the transformed variables of the VC-backed and non-VC-backed companies. The statistics are measured over the longitudinal data set. *Patents* and *Citations / Patents* represent the logarithmic transformation after adding one. *Age* is the logarithmic transformation after adding one to the age of a company since its incorporation. *Syndicate size* is the logarithmic transformation of the number of co-investors participating in a deal. Table 5 shows that the mean number of patents for the VC-backed group is 1.44, whereas the mean for the non-VC-backed group is 0.912. Conducting a one-sided *t*-test on the means confirms that this difference is significant ($t = 60.67$; $p < 0.001$). This also holds true for the *Citations / Patents* ($t = 43.44$; $p < 0.001$). In this sample, the total amount of VCs participating in a transaction varies from one to a maximum number of eight VCs. The non-VC-backed group does not produce data on syndicate size as they have not received any investment and therefore cannot be part of a syndicate.

The Appendix Table A.5 displays the pairwise correlations over the full sample. The correlations between the variables can be interpreted as an indicator for multicollinearity. One can observe that positive correlation between the explanatory variables and the dependent variables exist. The correlation between the independent variables *syndicate size* and *age* do not raise any concerns about multicollinearity as the correlation is 0.13.

Table 5: Descriptive Statistics

This table reports the descriptive statistics of the transformed variables.

	N	Min	Median	Mean	Max	Std. Deviation
VC-backed group						
Patents	24125	0	1.39	1.44	5.51	1.12
Citations / Patents	24125	0	0.29	0.62	4.87	0.79
Age	24125	0	1.95	1.77	3.33	0.73
Syndicate size	24125	0	0.00	0.41	2.08	0.50
Non-VC-backed group						
Patents	29659	0	0.69	0.91	6.29	0.85
Citations / Patents	29659	0	0.10	0.35	5.18	0.62
Age	29659	0	1.95	1.87	3.09	0.73

3.6.1 Empirical model

To answer the main research question, '*What is the effect of GVC investments on innovation in Europe?'* the hypotheses formulated in subsection 2.5 are tested by employing fixed effects regressions, in which each panel contains a maximum of 10 years around a VC investment. Each panel represents a unique VC investment in a start-up or SME. In other words, this study examines the effect of GVC investments on innovation.

The fixed effects method is favoured above the pooled OLS and random effects models, as the fixed effects control for time-invariant unobserved heterogeneity, endogeneity, and selection bias (Park, 2011; Imai & Kim, 2016). Notably, the pooled OLS and random effects models were examined as well. However, as the data is biased, the pooled OLS regressions provide unreliable coefficients and biased results. The fixed effects controls for this bias. Furthermore, random effects models assume that the independent variables are uncorrelated with the fixed effects and that no correlation exists between the error term and independent variables, which increases the sensitivity of the model to omitted variables (Park, 2011). The remainder of this subsection elaborates on the empirical models discussed to test each hypothesis, as there are different subsamples created to measure the effect of GVC investments on innovation.

To assess the first hypothesis, *GVC investments positively impact innovation*, a subsample with 3041 non-VC-backed companies and the 354 unique GVC investments is created. The following equation is employed to test the first hypothesis:

$$Innovation_{it} = \beta_0 + \beta_1 After_{it} + \beta_2 After_{it} * GVC_i + \beta_4\ Age_{it}\ + \sum_{j=2003}^{2020} Years_{j,it} + c_i + u_{it} \quad (1)$$

$Innovation_{it}$ represents the innovation at time *t* of a company that received a GVC investment or is non-VC-backed. The *t* represents one year of the 10-year observation period of each panel, starting with five years prior to the investment and ending five years after the investment. $Innovation_{it}$ represents the innovation measured through *Patents* and *Citations / Patents*, which are computed as discussed in subsection 3.6. $After_{it}$ equals 0 before the investment and equals 1 after the investment at time *t*, holding this value until five years after the investment time.

$After_{it} * GVC_i$ is an interaction variable, where GVC_i is 1 if the panel represents a GVC investment and 0 otherwise. This is the variable of interest as it measures the impact of a GVC investment on the innovation compared to the reference group. If the coefficient of β_2 is positive and significant, this indicates that the GVC investments lead to more innovation. Lastly, c_i captures the time invariant unobserved individual specific factors and remains constant before and after investment.

Age_{it} represents the age of a company since its incorporation in years at time *t*. $Years_{j,it}$ are dummies for the observational year *j* in the panel (i.e., if an investment occurs in 2009, the innovation of a company is observed from 2004 until 2014). By controlling for years, the results correct for trends over in time.

To test the second hypothesis, '*GVC investments impact innovation less than PVC investments'*, a subsample of GVC and PVC investments is created. This sample contains 354 GVC and 1132 PVC investments. For the third hypothesis, '*GVC investments impact innovation less than CVC investments'*, a subsample of GVC and CVC investments is created that contains 354 GVC and 271 CVC investments. Both hypotheses are tested by employing the following fixed effects model:

$$Innovation_{it} = \beta_0 + \beta_1 After_{it} + \beta_2 After_{it} * GVC_i + \beta_3\, Age_{it} + \beta_4\, Syndicate\ size_{it} + \sum_{j=2003}^{2020} Years_{j,it} + c_i + u_{it} \tag{2}$$

The set-up of equation (2) is similar to that of equation (1). However, it also includes another control variable, $Syndicate\ size_{it}$. This variable represents the number of co-investors participating in the investment. β_2 indicates the coefficient of interest as it measures the difference in the pre- and post-investment innovation between GVC and PVC investments, which allows the assessment of the second hypothesis. With regards to the third hypothesis, it represents the difference between GVC and CVC investments. If the coefficient β_2 is negative and significant, the hypothesis is supported.

To test the fourth hypothesis, *'Homogenous investments impact innovation less than mixed syndicate (heterogenous) investments',* PVC, GVC and CVC are considered as homogenous investments. PVC-GVC, PVC-CVC, GVC-CVC and PVC-GVC-CVC syndicates are clustered as heterogeneous (mixed syndicates) investments and serve as the reference group in this model. This results in the following equation:

$$Innovation_{it} = \beta_0 + \beta_1 After_{it} + \beta_2 After_{it} * Homogenous_i + \beta_3 Age_{it} + \beta_4\, Syndicate\ size_{it} + \sum_{j=2003}^{2020} Years_{j,it} + c_i + u_{it} \tag{3}$$

$Homogenous_i$ is 1 for homogenous investments and 0 for heterogenous investments. If the coefficient β_2 is negative and significant, the hypothesis is supported. All the hypotheses are tested over a three- and five-year post-investment period. Additionally, Table A.6 summarizes results of the Durbin–Wu–Hausman tests for the different equations for the five-year post-investment period. This test's results confirm that fixed effects model is more reliable than the random effects one. Chapter 4 discusses the results of the empirical analyses on the effect of GVC investments on innovation.

4 Results

This chapter discusses the results of the fixed effects panel data analyses for both the three- and five-year post-investment period. In Subsection 4.2, the robustness checks are discussed.

4.1 Results of fixed effects regressions

Table 6 reports the results for the three-year post-investment period, with patents serving as a measure of innovation. Each column presents the results of the fixed effects regressions with robust standard errors for each of the subsamples. Column (1) presents the results for GVC investments in non-VC-backed companies. Column (2) shows the findings comparing the GVC investments to PVC investments. Column (3) presents the comparisons of GVC and CVC investments and Column (4) the homogenous investments compared to heterogenous investments.

Table 6: Results of Fixed Effects Regressions on Patents Three Years Post Investment

The table displays the results of the fixed effects panel regressions (Columns 1-4) for each subsample three years after the investment. Each panel represents a unique VC investment in a company or a non-VC-backed company. The dependent variable is represented by the patents at time *t*. *After* is a dummy variable representing whether the period occurs after the investment. *After*GVC* represents the interaction between the after period and GVC investments. *After*Homogenous* represents the interaction between homogenous investments and the after period. *Age* represents the age of a company since incorporation. *Syndicate size* represents the number of co-investors. Year dummies are added to control for the observational year. Robust standard errors are used and reported in parentheses. ***, **, *, represent the statistical significance at the 1%, 5% and 10% level, respectively.

	(1) GVC vs. Non-VC-backed	(2) GVC vs. PVC	(3) GVC vs. CVC	(4) Homogenous vs. heterogenous
After	-0.011 (0.011)	0.010 (0.019)	0.071* (0.039)	0.051 (0.044)
*After * GVC*	0.264*** (0.033)	-0.038 (0.037)	-0.046 (0.051)	
*After*Homogenous*				-0.078* (0.042)
Age	0.096*** (0.022)	0.244*** (0.028)	0.282*** (0.040	0.259*** (0.022)
Syndicate size		0.079*	-0.090	0.076**
Year dummies	Yes	Yes	Yes	Yes
Constant	0.165*** (0.019)	-0.459*** (0.063)	-0.505*** (0.125)	-0.457*** (0.049)
Observations	26,076	11,205	4,536	19,111
R-squared	0.498	0.597	0.587	0.614
Adjusted R squared	0.498	0.596	0.585	0.613
VC groups	3,395	1,486	625	2,507
F-Value	633.66***	203.24***	86.56***	363.03***

The results in column (1) do not show significantly more innovation for all groups in the after period. However, GVC investments positively affect innovation in the post-investment period compared to that of the non-VC-backed reference group ($\beta = 0.264$, $p < 0.001$). This result supports the first hypothesis as well as the previous literature (Arqué-Castells, 2012; Bertoni et al., 2010; Bertoni & Tykvovà, 2015). Columns (2) and (3) test the second and third hypothesis, respectively.

The sign of the coefficients *After*GVC* in Columns (2) and (3) are, as expected, negative. However, both coefficients are not significant. Thus, the second and third hypotheses could not be confirmed based on these analyses; no evidence was found that GVC investments significantly differ from PVC and CVC investments in their ability to spur innovation in the three-year post-investment period. *Syndicate size* is positive and significant ($\beta = 0.079$, $p = 0.083$) in the second analysis, indicating a positive effect of the number of investors participating in an investment on innovation.

The fourth hypothesis is tested by the results reported in Column (4). No significant difference in innovation exists in the post-investment period for the whole subsample. However, homogenous investments do significantly underperform heterogenous investments in the three-year post-investment period ($\beta =-0.078$; $p = 0.064$). Therefore, the fourth hypothesis is accepted. The results in Column (4) further suggest that the number of co-investors positively affects the innovativeness of a company ($\beta = 0.076$, $p = 0.043$). Moreover, the age of the company positively and significantly impacts innovation in all four regressions. As VCs mainly invest in start-ups and SMEs, older companies may already be more innovative and file more patents than those companies that received funding at their incorporation and have not yet patented. Therefore, age is likely to positively affect innovation. For all models, the R-squared, which indicates how much of the variance in the dependent variable is explained by the model, is considerably high. The adjusted R-squared approaches the R-squared across all models. To further examine the relationship between GVC investments and innovation and test the hypotheses, the same models are employed for the five-year post-investment period, with the results are presented in Table 7.

The results presented in Table 7 Column (1) suggest that for the five-year post-investment period, GVC investments positively affect innovation compared to the reference group ($\beta =0.274$; $p < 0.001$). This result supports the first hypothesis. Model (2) indicates that in the five-year post-investment period, innovation significantly increases ($\beta =0.103$; $p < 0.001$). However, the coefficient of *After*GVC* is insignificant, thus suggesting that GVC investments do not result in less innovation than PVC investments. Therefore, the second hypothesis cannot be accepted or rejected. In the subsample consisting of GVC and CVC investments, the results show that the GVC investments do not significantly differ from CVC investments in their ability to create innovation. The third hypothesis cannot be accepted or rejected based on these results. Column (4) compares the innovativeness of homogenous and heterogenous investments. The β-coefficient supports hypothesis 4 and is significant at the five percent level ($\beta =-0.096$; $p = 0.030$).

Table 7: Results of Fixed Effects Regressions on Patents Five Years Post Investment

The table displays the results of the fixed effects panel regressions (Columns 1-4) for each subsample five years after the investment. Each panel represents a unique VC investment in a company or a non-VC-backed company. The dependent variable is represented by the patents at time *t*. *After* is a dummy variable representing whether the period occurs after the investment. *After*GVC* represents the interaction between the after period and GVC investments. *After*Homogenous* represents the interaction between homogenous investments and the after period. *Age* represents the age of a company since incorporation. *Syndicate size* represents the number of co-investors. Year dummies are added to control for the observational year. Robust standard errors are used and reported in parentheses. ***, **, *, represent the statistical significance at the 1%, 5% and 10% level, respectively.

	(1) GVC vs. Non-VC-backed	(2) GVC vs. PVC	(3) GVC vs. CVC	(4) Homogenous vs. Heterogenous
After	-0.004 (0.012)	0.103*** (0.021)	0.160*** (0.043)	0.157*** (0.046)
*After*GVC*	0.274*** (0.035)	-0.046 (0.039)	-0.073 (0.054)	
*After*Homogenous*				-0.096** (0.044)
Age	0.072*** (0.021)	0.309*** (0.027)	0.343*** (0.039)	0.324*** (0.021)
Syndicate size		0.081* (0.047)	-0.084 (0.122)	0.078** (0.039)
Year dummies	Yes	Yes	Yes	Yes
Constant	0.190*** (0.018)	-0.354*** (0.065)	-0.424*** (0.127)	-0.353*** (0.051)
Observations	32,866	14,177	5,786	24,125
R-squared	0.545	0.619	0.615	0.636
Adjusted R-squared	0.545	0.619	0.613	0.636
VC groups	3,395	1,486	625	2,507
F-value	731.09***	219.09***	93.39***	387.71***

In addition, in homogenous and heterogenous investments, the syndicate size positively impacts the innovation of a company (β =0.078; p = 0.047). The age of the company positively affects innovation in all models. As previously mentioned, one should keep in mind that VCs focus on young innovative companies and SMEs.

To summarise, Tables 6 and 7 provide the results on the impact of GVC investments on innovation as measured by patent filings. Both the results for the three- and five-year post-investment period support the first hypothesis. The results do not suffice for the acceptance or rejection of the second and third hypotheses, as these analyses did not find a significant difference in the success of GVC investments versus PVC or CVC investments. The fourth hypothesis is accepted, as homogenous investments underperform heterogenous investments, supporting the theory that combining different types of VCs will ultimately lead to more innovation, as different governance structures, investment goals and investment horizons could prove beneficial for supporting innovation (Bertoni & Tykvovà, 2015).

The results reported in Tables 6 and 7 measured innovation based on the number of patents. However, one could argue that filing a patent does not itself per se indicate innovations with economic value or high quality. Therefore, a second set of fixed effects regressions are employed. However, these regressions contain *Citations / Patents* as the dependent variable. Since citations indicate the quality of a patent, and filing more patents that do not receive citations decreases this ratio, it therefore serves as a tighter measure of innovation. The results for the three-year post-investment period are shown in Table 8 and for the five-year post-investment period in Table 9. All independent variables and sub-samples remain the same as previous models.

Table 8 presents the results for the three-year post-investment period. Column (1) presents evidence favouring the first hypothesis as *After*GVC* has a positive and significant coefficient ($\beta = 0.154$; $p < 0.001$). As in the previous analyses, the first hypothesis is accepted. The R-squared of the first model is 0.132. In the second model, interestingly, the negative insignificant coefficient *After*GVC* that was reported in Tables 6 and 7 has become positively significant ($\beta = 0.068$, $p = 0.060$). The finding contradicts the second hypothesis and indicates that GVC investments do positively affect innovation more than PVC investments. As this research defined VC programs from public institutions focusing on quality innovation (universities) as GVCs, the focus on quality innovation is probably more pronounced than for PVCs. As well, no significantly positive effect exists for the whole subsample in Column (2) in the post-investment period. The R-squared for the second model is 0.185.

The third hypothesis is neither accepted nor rejected based on the analysis presented in column (3) of Table 6. Similar to the above results, the coefficient has become positive in this table; however, it is insignificant ($\beta = 0.045$; $p = 0.010$). Furthermore, the post-investment period does not seem to be more innovative than the pre-investment period for the whole subsample. The last column shows no significant difference between homogenous and heterogenous VC investments. The fourth hypothesis cannot be accepted or rejected based on these results. Age positively and significantly impacts innovation in all regressions. The R-squared is 0.212 for the third and 0.187 for the fourth model. Interestingly for Columns (2) to (4) the coefficients of the post investment period do not indicate there is more quality innovation for the whole subsample post-investment. This suggests that for the three-year post-investment VC investments do not affect innovation measured by *Citations / Patents.*

The results for the five-year post-investment period are shown in Table 9. It is immediately obvious that the results are similar to those for the three-year post-investment period. Once again, the *After*GVC* coefficient is positive and significant in the first column, supporting the first hypothesis. The R-squared is 0.133. The second column shows that GVC investments display a significantly larger effect on innovation than PVC investments ($\beta = 0.067$; $p = 0.068$). This contradicts the second hypothesis. Column (3) displays the results testing the third hypothesis. Both *After* and *After*GVC* are insignificant.

Table 8: Results of Fixed Effects Regressions on Citation Weighted Patents Three Years Post Investment

The table displays the results of the fixed effects panel regressions (Columns 1-4) for each subsample three years after the investment. Each panel represents a unique VC investment in a company or a non-VC-backed company. The dependent variable is represented by the citation-weighted patents of a company at time *t*. *After* is a dummy variable representing whether the period occurs after the investment. *After*GVC* represents the interaction between the after period and GVC investments. *After*Homogenous* represents the interaction between homogenous investments and the after period. *Age* represents the age of a company since incorporation. *Syndicate size* represents the number of co-investors. Year dummies are added to control for the observational year. Robust standard errors are used and reported in parentheses. ***, **, *, represent the statistical significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)
	GVC vs. Non-VC-backed	GVC vs. PVC	GVC vs. CVC	Homogenous vs. Heterogenous
After	0.019**	-0.029	0.013	0.010
	(0.010)	(0.018)	(0.034)	(0.040)
After GVC*	0.154***	0.068*	0.045	
	(0.034)	(0.036)	(0.045)	
*After*Homogenous*				-0.005
				(0.037)
Age	0.038*	0.249***	0.180***	0.237***
	(0.020)	(0.027)	(0.043)	(0.021)
Syndicate size		0.072*	0.064	0.034
		(0.039)	(0.090)	(0.040)
Year dummies	Yes	Yes	Yes	Yes
Constant	0.089***	-0.096	-0.018	-0.014
	(0.017)	(0.075)	(0.096)	(0.053)
Observations	26,076	11,205	4,536	19,111
R-squared	0.132	0.185	0.212	0.187
Adjusted R-squared	0.131	0.184	0.208	0.186
VC groups	3,395	1,486	625	2,507
F-value	88.54***	33.98***	15.49***	57.84***

This result indicates more innovation does not occur after the GVC and CVC investments. In addition, GVC and CVC do not differ, based on this analysis, in their ability to create innovation. As most CVCs are operating in a strategic perspective for corporates, CVCs invest in high-quality companies. The difference in innovation between the GVC and PVC investments does not significantly differ from zero. Column (4) presents the results of homogenous and heterogenous investments; while the sign of *After*Homogenous* is expected, the coefficient is insignificant. Both the results in Columns (3) and (4) do not indicate more innovation in the post-investment period. They also demonstrate that innovation from GVC investments does not significantly differ from CVC investments and

Table 9: Results of Fixed Effects Regressions on Citation Weighted Patents Five Years Post Investment

The table displays the results of the fixed effects panel regressions (Columns 1-4) for each subsample five years after the investment. Each panel represents a unique VC investment or a non-VC-backed company. The dependent variable is represented by the citation-weighted patents at time *t*. The dependent variable is represented by the patents at time *t*. *After* is a dummy variable representing whether the period occurs after the investment. *After*GVC* represents the interaction between the after period and GVC investments. *After*Homogenous* represents the interaction between homogenous investments and the after period. *Age* represents the age of a company since incorporation. *Syndicate size* represents the number of co-investors. Year dummies are added to control for the observational year. Robust standard errors are used and reported in parentheses. ***, **, *, represent the statistical significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)
	GVC vs. Non-VC-backed	GVC vs. PVC	GVC vs. CVC	Homogenous vs. Heterogenous
After	0.043***	-0.001	0.030	0.036
	(0.009)	(0.017)	(0.032)	(0.040)
*After*GVC*	0.144***	0.067*	0.035	
	(0.034)	(0.037)	(0.046)	
*After*homogenous*				-0.001
				(0.037)
Age	0.017	0.252***	0.180***	0.243***
	(0.019)	(0.024)	(0.039)	(0.019)
Syndicate size		0.074*	0.059	0.031
		(0.039)	(0.089)	(0.034)
Year dummies	Yes	Yes	Yes	Yes
Constant	0.107***	-0.051	0.008	0.024
	(0.016)	(0.075)	(0.102)	(0.054)
Observations	32,866	14,177	5,786	24,125
R-squared	0.133	0.186	0.217	0.187
Adjusted R-squared	0.133	0.185	0.214	0.186
VC groups	3,395	1,486	625	2,507
F-value	80.97***	33.95***	15.29***	56.31***

homogeneous investments do not significantly differ from heterogenous investments. Therefore, the third and fourth hypothesis could not be accepted based on these results.

Overall, the results discussed show some interesting findings on the effect of GVC investments compared to other VC investments on innovation. All analyses show that after a GVC investment, innovation increases significantly compared to the non-VC-backed group. The analyses employing the subsamples of GVC and PVC investments do not indicate that GVC investments impact innovation less than PVC investments. Moreover, the results reported in Tables 8 and 9 suggest that GVC investments increase innovation more than PVC investments. This research is the first to examine the difference in the effect of GVC and CVC investments on innovation. All the results investigating their differences are insignificant, so this sample does not indicate a difference in innovation created by the GVCs versus the

CVCs. As for type of investment, the results suggest that homogenous investments are less successful in creating innovation than heterogenous investments. However, this relationship becomes insignificant when using the citation-weighted innovation measure.

4.2 Robustness

To further justify the results presented in subsection 4.1 two robustness checks are conducted to test whether the results remain the same in different settings. The results of the different robustness checks can be found in the appendix.

This research examines the VC market in Europe. As the UK represents 27% of the VC investments included in this research, the results could be driven by this specific country. Therefore, the analyses are again performed after excluding the UK from the sample. These results are reported in Tables A.7 and A.8, which use innovation based on patents and citation-weighted patents as the dependent variables, respectively. As can be observed by Table A.7, the signs of the coefficients are similar to those reported in the main analysis. However, in Columns (2) and (3) of Table A.7, the *After*GVC* coefficient becomes significant. This result illustrates that upon excluding the UK, GVC investments underperform PVC and CVC in terms of innovation. The UK is a developed VC market; however, their VCs may be less interested in innovation. To partly justify this conclusion, a *t*-test on number of patents among the non-VC-backed group was conducted. The *t*-test shows that the UK files fewer patents than the other European countries in this sample ($t = 10.29$; $p < 0.001$). This result indicates that UK companies are generally less innovative in terms of patenting. So, the dataset is sensitive to the UK as a larger spread in the number of patents exists. The VC market of the UK probably differs from the rest of the EU, and therefore the results become more pronounced in the robustness check. Table A.8 reports the robustness check when measuring innovation based on citation-weighted patents. For this quality-weighted measure, the results reported in Columns (1)-(4) are robust upon excluding the UK from the sample.

As previously discussed, the sample mainly consists of companies and investments made in the manufacturing and services industries (Table A.4). The results may be influenced by the focus on this sector. Sorting the sample on the two-digit SIC codes shows that more than 78% of the sample consists of companies active in industries with SIC codes 28, 36, 38, 73 and 87[2]. Investments are only considered if a company has filed for at least one patent between five years prior to and five years after the investment. Therefore, industries in which filing patents is more common are more common in this sample. To check whether the results are driven by these industries, these five industries are omitted from the sample. Omitting these industries reduces the sample size. However, the subsamples remain large enough to conduct analyses. The results of these robustness checks are presented in Tables A.9 and A.10.

[2] 28: Chemicals, 36: Electronical equipment, 38: Measuring instruments, 73: Business services, and 87: Engineering services

The results presented in Table A.9 Columns (1), (2), and (3) are robust to the exclusion of the dominant industries. For the subsample with homogenous and heterogenous investments, the underperformance of homogenous investments (relative to the heterogenous investments) becomes insignificant. This indicates that the results of the fourth hypothesis's assessment could partly be driven by these five industries. The robustness analyses on the citation weighted patents reported in Table A.10 shows that the results are robust in terms of the sign of the coefficients *After*GVC* and *After*Homogenous.* However, the results in Column (1) of Table A.10 suggest that the results of GVC investments are driven by the industries that are excluded from the analysis.

All in all, the results reported in Subsection 4.1 are not particularly robust to the exclusion of the UK and dominant industries from the sample, particularly for the UK, which appears to drive the results for the subsamples of GVC, PVC, and CVC investments.

5 Limitations

Before concluding this paper, the limitations and shortcomings of this study should be acknowledged. It employs fixed effects panel data regressions to control for time-invariant unobserved heterogeneity, endogeneity, and selection bias. The fixed effects models are preferable to the OLS and random effects models for the analysis of the impact of GVC investments on innovation. However, as this research examines the effect of GVC investments on innovation, only a limited number of control variables could be used. To be more precise, because of the time period chosen and the lack of available company and investment data, this research fails to control for several factors that might bias the estimations. Company-level variables such as assets and R&D expenditures were unavailable for this research. However, since VCs mainly invest in start-ups and SMEs, the size of company is less important, as very large companies are not likely to receive VC investments. Most studies on VC have access to private databases that are not available to master's students (such as the VICO database) or focuses on companies that eventually go public, allowing them to include more control variables. However, as this research focuses on a new field of research that also only includes private companies, data limitations are not uncommon; this fact has already been addressed in the previous literature (Brander et al., 2008).

In addition, the use of patents as a proxy for innovation is widely accepted in the literature, although only EPO and WIPO patents were included because the standards of these patents remain high quality across countries. Some industries patent more than other industries and laws on the obtaining of patents differ across industries. Companies that are innovative, but simply do not patent are not considered in this research. This could bias the results. Moreover, examining the citation-weighted patent measure in this research raises the possible concern that patents that are filed earlier in time are more likely to obtain forward citations than patents filed in recent years, which could bias the results considering the recent observation period. Furthermore, this study uses patent applications rather than granted patents. However, not all patents are already granted. Even though the recent observation period partially justifies the use of patent applications, granted patents might be better scrutinized and therefore a more reliable proxy for innovation. However, the length of the observational period does not allow the use of granted patents as the granting process takes longer than the five-year post-investment period. Another limitation of using patent applications is that companies might file fewer patents after the investment period than they did before as they have more focused research programs. This may reduce the growth in patents but not the innovativeness of a company.

Although the fixed effects analyses in this study control for endogeneity, heterogeneity, and selection bias, not all endogeneity concerns about the relationship between VC investments and innovation could be considered. One endogeneity concern that might still exist is the problem of simultaneous causality. This potential reverse causality between VC investments and innovation could be accounted for by employing instrumental variables analyses (Samila & Sorenson, 2010).

6 Conclusion

This research examined the relationship between GVC investments and the effect of innovation after the investment. The effect of GVC investments was first examined by comparing GVC investments with a non-VC-backed group. As well, the difference between various types of VC investments was assessed by comparing GVC with PVC and CVC investments. In addition, the difference between homogenous and heterogenous investments was examined. This paper mainly investigates the research question, '*What is the effect of GVC investments on innovation in Europe?*'

To test the hypotheses, panel data fixed effects models for 2507 different VC investments that occurred between 2008-2015 were used. The impact of the investments was measured by following the innovation activity of the investees that had filed at least one patent in the five years prior to and after their investment. To specifically test the impact of GVC investments on innovation, subsamples were created to measure the impact of GVC investments regarding non-VC-backed companies, PVC investments, and CVC investments. The composition of the non-VC-backed group was based on the propensity score matching technique to decrease the selection bias and select companies that could have received funding as well. The hypotheses are tested on using both total number of patents and the citation-weighted patents as the dependent variables for three and five years after the investment.

The first hypothesis to be tested was '*GVC investments positively impact innovation'*. This hypothesis was assessed by measuring the difference in innovation of GVC investments with the non-VC-backed group. The results show that innovation, as measured by patents and citation-weighted patents, are higher after a GVC investment compared to non-VC-backed group. This holds for both the three- and five-year post-investment period and indicates that GVC investments do positively impact innovation. The finding supports the theoretical argument that governments spur innovation and therefore could justify the existence of GVCs (Kraemer-Eis et al., 2018).

The second hypothesis '*GVC investments impact innovation less than PVC'* was tested by creating a subsample of GVC and PVC investments. The analyses with the patents as the dependent variable show no significant difference in the effect on innovation after investment of GVC versus PVC investments. However, once innovation is measured as citation-weighted patents, GVC investments demonstrate a greater effect on innovation than PVC investments. This finding suggests that in this sample innovations are of higher quality for the companies that received a GVC investment. However, the results are most likely driven by the industries chosen by GVCs to invest in, as the results are not robust once certain industries are excluded. The second hypothesis is partly rejected; however, the results are insufficient to fully reject or accept this hypothesis.

The third hypothesis '*GVC investments impact innovation less than CVC'* was examined by comparing GVC and CVC investments. This is a novelty in the VC literature. However, the results presented do not indicate that the two VC types differ in their ability to create innovation. The third hypothesis is not rejected or accepted based on the results in this research.

The fourth hypothesis *'Homogenous investments impact innovation less than mixed syndicate (heterogenous) investments'* was examined in the full sample of 2507 investments and creating two groups of homogenous and heterogenous investments. The results are accepted when innovation is measured based on patents for both 3 and 5 years after investment period. There is no significant difference found between the two when controlling for the quality of patents, however, the coefficients remain negative. This hypothesis is accepted based on the first analyses, however, the results based on the quality weighted innovation does provide significant evidence in favour of this hypothesis. Therefore, based on the results, this hypothesis can only partially be accepted.

In the light of above, GVC has a positive effect on innovation based on the findings in this research. Furthermore, the results do not suggest that GVC underperform in terms of innovation compared to PVC and CVC. However, it is most likely that in light of the robustness analyses, other factors in addition to the GVC investment, such as the industry or country, contribute to innovation. The concerns of simultaneous causality of innovation and VC remains.

This study aims to examine the impact of GVC investments on the innovation of companies in Europe in the years following investment. Despite the employment of fixed effects models, not all endogeneity concerns could be accounted for. Nonetheless, this study contributes to existing research by attempting to address the impact of GVC investments in Europe. Furthermore, this research represents one of the first attempts on an industry- and country-wide European scale to assess the success of GVC investments on innovation in Europe. Furthermore, to the best of my knowledge, this study is the first to examine the difference between GVC and CVC in a single analysis. However, further research and more detailed private databases are required to arrive at more conclusive findings regarding the impact of GVC on innovation. More extensive databases are now being developed for VC and innovation, for example the RISIS project. As the European VC market constantly changes across industries and countries, numerous possibilities exist to further examine the differences between GVCs and other VCs. For example, measuring innovation based on other innovation measures than those used in this research, such as R&D expenditures. In addition, future research should, if allowed by the data, distinguish between different types of GVC and their investment objectives. Lastly, the success of GVC programs in Europe could also be assessed by their ability to create employment.

7 Bibliography

Alperovych, Y., Groh, A., & Quas, A. (2015). When can government venture capital funds bridge the equity gap? Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=27118061

Arqué-Castells, P. (2012). How venture capitalists spur invention in Spain: Evidence from patent trajectories. *Research Policy*, 897-912.

Artz, K., Norman, P., Hatfield, D., & Cardinal, L. (2010). A longtitudinal study of the impact of R&D, patents, and product innovation on firm performance. *Journal of Product Innovation Management*, *27*(5), 725-740.

Backes-Gellner, U., & Werner, A. (2007). Entrepreneurial signaling via education: A success factor in innovative startups. *Small Business Economics, 29*(1-2), 173-190.

Bertoni, F., & Tykvovà, T. (2012). Which form of venture capital is most supportive of innovation? *ZEW Discussion Papers, 12*(018).

Bertoni, F., & Tykvovà, T. (2015). Does govermental venture capital spur invention and innovation? Evidence from young European biotech companies. *Reserach Policy, 44*(4), 925-935.

Bertoni, F., Colombo, M., & Quas, A. (2015). The patterns of venture capital investments in Europe. *Small Business Economics*, *45*(3), 543-560.

Bertoni, F., Croce, A., & D'Adda, D. (2010). Venture capital investments and patenting activity of high tech start-ups: a micro econometric firm-level analysis. *Venture Capital: an International Journal of Entrepreneurial Finance*, 307-326.

Bottazzi, L., & Da Rin, M. (2002). Venture capital in Europe and the financing of innovative companies. *Economic Policy, 17*(34), 229-270.

Brander, J., Du, Q., & Hellmann, T. (2015). The Effects of Government-Sponsored Venture Capital: International Evidence. *Review of Finance*, *19*(2), 571-618.

Brander, J., Egan, E., & Hellmann, T. (2008). Government sponsored versus private venture capital: Canadian evidence. *the National Bureau of Economic Research*, 275-320.

Bruton, G. D., Fried, V., & Manigart, S. (2005). Institutional influences on the worldwide expansion of venture capital. *Entrepreneurship Theory and Practice*, 737-760.

Caselli, S., Gatti, S., & Perrini, F. (2008). Are Venture Capitalists a Catalyst for Innovation? *European Financial Management*, *15*(1), 92-111.

Chemmanur, T., Loutskina, E., & Tian, X. (2014). Corporate venture capital, value creation, and innovation. *The Review of FInancial Studies, 27*(8), 2434-2473.

Colombo, M., Cumming, D., & Vismara, S. (2016). Governmental venture capital for young innovative firms. *The Journal of Technology Transfer, 41*(1), 10-24.

Cumming, D., Grilli, L., & Murtinu, S. (2017). Governmental and independent venture capital investments in Europe: A firm-level performance analysis. *Journal of Corporate Finance*, 439-459.

Da Rin, M., Hellmann, T., & Puri, M. (2013). A survey of venture capital research. InG. Constantinides, M. Harris, & R. Stulz (Eds.). *Handbook of the Economics of Finance, 2*, 573-648.

Dixon, R. (1991). Venture Capital and the Appraisal of Investments. *International Journal of Management Science*, 333-344.

Dushnitsky, G. (2006). Corporate venture capital: Past evidence and future directions. *Oxford Handbook of Entrepreneurship Oxford University Press*, 387-431.

Engel, D., & Keilbach, M. (2007). Firm-level implications of early stage venture capital investment - an empirical investigation. *Journal of Empirical Finance*, 150-167.

European Commission. (2020, May 24). *Research and Innovation Observatory – Horizon 2020 Policy Support Facility*. Retrieved from rio.jrc.ec.europa.eu: https://rio.jrc.ec.europa.eu/stats/venture-capital-investments

Gompers, P. (1996). Grandstanding in the venture capital industry. *Journal of FInancial Economics*, 133-156.

Gompers, P., & Lerner, J. (1999). What drives venture capital fundraising? *the National Bureau of Economic Research*. Retrieved from https://www.nber.org/papers/w6906

Griliches, Z. (1992). The search for R&D spillovers. *Scandinavian Journal of Economics*, 29-47.

Griliches, Z. (1998). Patent statistics as economic indicators: a survey. *Journal of Economic Literature, 28*(4), 1523-1543.

Grilli, L., & Martinu, S. (2014). Government, venture capital and the growth of European high-tech entrepreneurial films. *Research Policy, 43*(9), 1523-1543.

Hagedoorn, J., & Cloodt, M. (2003). Measuring innovative performance: is there an advantage of using multiple indicators? *Research Policy, 32*(8), 1365-1379.

Hall, B., Griliches, Z., & Hausman, J. (1986). Patents and R and D: Is there a lag? *International Economic Review, 27*(2), 265-283.

Hellmann, T., & Puri, M. (2000). The interaction between product markets and financing strategy: the role of venture capital. *Review of Financial Studies, 7*(6), 959-984.

Imai, K., & Kim, I. (2016). When Should We Use Linear Fixed Effects Regression Models for Causal Inference with Longitudinal Data? *Political Methodology Summer Meeting* (pp. 1-37). Rice University. Retrieved from https://imai.fas.harvard.edu/talk/files/polmeth16.pdf

Invest Europe. (2020). *Investing in Europe: Private Equity Activity 2019.* Invest Europe Research. Retrieved from https://www.investeurope.eu/research/data-and-insight/

Jääskeläinen, M., Maula, M., & Murray, G. (2007). Profit distribution and compensation structures in publicly and privately funded hybrid venture capital funds. *Research Policy*, 281-315.

Katila, R. (2000). Using patent data to measure innovation performance. *International Journal of Business Performance Management*, 180-193.

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

Kraemer-Eis, H., Signore, S., & Prencipe, D. (2018). The European venture capital landscape: an EIF perspective. *EIF Research & Market Analysis*, *1*.

Leleux, B., & Surlemont, B. (2003). Public versus private venture capital: seeding or crowding out? A pan european analysis. *Journal of Business Venturing*, *18*(1), 81-104.

Lerner, J. (2002). Boom and bust in the venture capital industry and the impact on innovation. *Harvard NOM Research Paper*.

Mansfield, E. (1986). Patents and innovation: an empirical study. *Management Science*, *32*(2), 173-181.

Mason, C., & Harrison, R. (1997). Busines Angel Networks and the Development of the Invformal Venture Capital Market in the UK: Is There Still a Role for the Public Sector. *Small Business Economics, 24*(2), 111-123.

Mason, C., & Harrison, R. T. (1995). Closing the regional equity capital gap: The role of informal venture capital. *Small Business Economics, 7*(2), 153-172.

Park, H. (2011). Practical guides to panel data modeling: a step-by-step analysis using stata. *Public Analysis Program; Graduate School of International Relations*, 1-52.

Park, S., & LiPuma, J. (2020). New venture internationalization: The role of venture capital types and reputation. *Journal of World Business*, 1-10.

Popov, A., & Roosenboom, P. (2012). Venture capital and patented innovation: evidence from Europe. *Economic Policy, 27*(71), 447-482.

Rajan, R., Servaes, H., & Zingales, L. (2000). The cost of diversity: The diversification discount and inefficient investment. *Journal of Finance*, 599-631.

Sahlman, W. (1990). The structure and governance of venture-capital organizations. *Journal of Financial Economics*, *27*(2), 473-521.

Samila, S., & Sorenson, O. (2010). Venture Capital as a catalyst to commercialization. *Research Policy*, 1348-1360.

Seru, A. (2014). Firm boundaries matter: Evidence from conglomerates and R&D activity. *Journal of Financial Economics*, 381-405.

Tykvovà, T., Borrel, M., & Kroencke, T. (2012). *Potential of venture capital in the european union.* Tech. rep, Directorate-General for Internal Policies, European Parliament. Retrieved from http://www.europarl.europa.eu/studies

Ueda, M., & Hirukawa, M. (2011). Venture Capital and Innovation: Which is First? *Pacific Economic Review, 16*(4), 421-465.

Wilson, K. (2015). Policy lessons from financing innovative firms. *OECD Science, Technology and Industry Policy Papers, 24*.

Appendix

Table A.1: List of GVC Firms
List with all identified GVCs in this research.

Austria Wirtschaftsservice GmbH	Austria	Dublin Business Innovation Centre	Ireland
OOE Hightechfonds GmbH	Austria	Enterprise Ireland	Ireland
Tecnet Equity NOE Technologiebeteiligungs Invest	Austria	Western Development Commission	Ireland
Brussels I3 Fund NV	Belgium	Friulia Veneto Sviluppo SGR SpA	Italy
LRM NV	Belgium	Vertis SGR SpA	Italy
NIVELINVEST SA	Belgium	Brabantse Ontwikkelings Maatschappij NV	Netherlands
ParticipatieMaatschappij Vlaanderen NV	Belgium	Newion Investments BV	Netherlands
Societe Regionale D'Investissement de Wallonie SA	Belgium	NV Industriebank Liof	Netherlands
Sopartec SA	Belgium	Participatiemaatschappij Oost Nederland NV	Netherlands
Srib	Belgium	Zeeuws Investeringsfonds BV	Netherlands
Vlaamse Investeringvennootschap NV	Belgium	Energy Future Invest As	Norway
Pre-Seed Innovation A/S	Denmark	Fjord Invest Management AS	Norway
VAEKSTFONDEN	Denmark	Hafslund Handel AS	Norway
Eesti Arengufond	Estonia	Investinor AS	Norway
Innovaatiorahoituskeskus Business Finland	Finland	Portugal Capital Ventures Sociedade de Capital de Risco SA	Portugal
Suomen Teollisuussijoitus Oy	Finland	Gestion De Capital Riesgo Del	Spain
Veraventure Oy	Finland	Inversion y Gestion de Capital de Riesgo de Andalucia SAU	Spain
VTT Ventures Oy	Finland	Sociedad de Desarrollo de Navarra SL	Spain
Aquitaine Creation Investissement SAS	France	Unirisco Galicia SCR SA	Spain
Bpifrance Investissement SASU	France	Almi Invest AB	Sweden
CDC Climat SA	France	Fouriertransform AB	Sweden
Cea Investissement SA	France	GU Ventures AB	Sweden
Poitou-Charentes Innovation SAS	France	Industrifonden	Sweden
Sem Genopole SA	France	Inlandsinnovation AB	Sweden
Supernova Invest SAS	France	KTH-Chalmers Capital KB	Sweden
Bayern Kapital GmbH	Germany	Lund University	Sweden
BC Brandenburg Capital GmbH	Germany	Sahlgrenska Science Park AB	Sweden
Beteiligungsfonds Wirtschaftsfoerderung Mannheim	Germany	Sparbanksstiftelsen Norrlands Riskkapitalstiftelse	Sweden
Bm T Beteiligungsmanagement	Germany	TeknoSeed AB	Sweden
CFH Beteiligungsgesellschaft mbH	Germany	Cambridge Innovation Capital Manager Ltd	United Kingdom
Genius Venture Capital GmbH	Germany	DBW FM Ltd	United Kingdom
High Tech Gruenderfonds Management GmbH	Germany	Development Bank of Wales Public Ltd Co	United Kingdom
IBB Beteiligungs GmbH	Germany	Highland Venture Capital	United Kingdom
IFB Innovationsstarter GmbH	Germany	Invest Northern Ireland	United Kingdom
Innogy Venture Capital GmbH	Germany	IP Group PLC	United Kingdom
Investitions Strukturbk Rhein Pfalz GmbH	Germany	Javelin Ventures Ltd	United Kingdom
KfW	Germany	National Endowment for Science Technology and the Arts	United Kingdom
Life Science Fonds Esslingen Verwaltungs GmbH	Germany	Oxford University	United Kingdom
MBG Baden-Wuerttemberg GmbH	Germany	Oxford University Innovation Ltd	United Kingdom
Mvc Unternehmensbeteiligungsgesellschaft Mbh	Germany	Partnerships Uk PLC	United Kingdom
NRW Bank	Germany	Qinetiq Ventures Ltd	United Kingdom
Saarlandische Wagnisfinanzierungsgesellschaft Mbh	Germany	Qubis Ltd	United Kingdom
Statkraft Ventures GmbH	Germany	Scottish Enterprise Glasgow	United Kingdom
S-Unternehmensbeteiligungsgesellschaft der Sparkasse	Germany	Sussex Place Ventures Ltd	United Kingdom
S-Venture Capital Dortmund GmbH	Germany	Technology Strategy Board	United Kingdom
Unternehmertum GmbH	Germany	University of Edinburgh	United Kingdom
Nyskopunarsjodur	Iceland	Viking Fund	United Kingdom
Act Venture Capital Ltd	Ireland		

Table A.2: Probit Propensity Score Matching

This table provides an overview of the propensity score matching for assigning propensity scores to the different companies and thus the likelihood of receiving funding. The variables included are *Region* representing the region where the company is active; based on NUTS level 1. *Company size* represents the size of the company as categorical variable. *Siccode* is 2 digits SIC code of the industry the company is active in. *Age* is the age of the company since incorporation. The analysis is conducted in a cross-sectional setting. In total 14.604 observations were included in the matching procedure. The column *P>Z* represents the *P*-values for each variable. An insignificant value means that the VC backed companies do not differ from non-VC-backed companies based on this variable.

Number of observations	14,604
LR chi2	4155.81
Prob>chi2	0.000
Pseudo R2	0.3103

VC backed	**Coef.**	**Std.Err.**	**z**	**P>z**	**[95% Confidence Interval]**	
Region						
AT2	-0.897	0.279	-3.210	0.001	-1.445	-0.349
AT3	-0.700	0.206	-3.390	0.001	-1.104	-0.296
BE1	1.043	0.313	3.330	0.001	0.429	1.657
BE2	0.154	0.163	0.940	0.345	-0.166	0.474
BE3	-0.090	0.229	-0.390	0.694	-0.539	0.359
DE1	-0.615	0.154	-3.980	0.000	-0.917	-0.312
DE2	-0.011	0.142	-0.070	0.941	-0.288	0.267
DE3	0.386	0.168	2.290	0.022	0.055	0.716
DE4	0.457	0.197	2.320	0.020	0.072	0.843
DE6	-0.731	0.262	-2.780	0.005	-1.245	-0.216
DE7	-0.574	0.193	-2.970	0.003	-0.952	-0.196
DE8	-0.035	0.283	-0.120	0.901	-0.591	0.520
DE9	-0.409	0.196	-2.090	0.037	-0.793	-0.025
DEA	-0.158	0.146	-1.080	0.279	-0.444	0.128
DEB	-0.615	0.258	-2.380	0.017	-1.121	-0.109
DEC	0.215	0.290	0.740	0.457	-0.352	0.783
DED	0.016	0.175	0.090	0.928	-0.328	0.359
DEE	-0.525	0.261	-2.010	0.044	-1.037	-0.014
DEF	-0.685	0.277	-2.480	0.013	-1.228	-0.143
DEG	-0.112	0.209	-0.540	0.591	-0.521	0.297
DK0	0.168	0.144	1.170	0.244	-0.114	0.450
EE0	-1.229	0.510	-2.410	0.016	-2.229	-0.228
ES1	-0.895	0.362	-2.470	0.013	-1.604	-0.186
ES2	-0.448	0.192	-2.340	0.019	-0.823	-0.072
ES3	-0.685	0.222	-3.080	0.002	-1.120	-0.249
ES4	-0.355	0.299	-1.190	0.234	-0.940	0.230
ES5	-0.413	0.169	-2.440	0.015	-0.745	-0.081
ES6	-0.721	0.281	-2.560	0.010	-1.272	-0.169
FI1	0.168	0.147	1.140	0.253	-0.120	0.455
FR1	0.906	0.152	5.950	0.000	0.607	1.204
FRB	-0.503	0.408	-1.230	0.218	-1.304	0.297
FRC	0.579	0.331	1.750	0.080	-0.070	1.228
FRD	0.849	0.302	2.810	0.005	0.257	1.441
FRE	0.522	0.240	2.180	0.029	0.052	0.991
FRF	0.526	0.235	2.240	0.025	0.066	0.987
FRG	0.269	0.249	1.080	0.280	-0.219	0.756
FRH	0.858	0.255	3.370	0.001	0.359	1.357
FRI	0.652	0.242	2.690	0.007	0.178	1.127
FRJ	0.715	0.205	3.490	0.000	0.314	1.116
FRK	0.646	0.166	3.890	0.000	0.321	0.972
FRL	0.603	0.187	3.230	0.001	0.237	0.969
HU1	-1.032	0.359	-2.870	0.004	-1.736	-0.327
HU2	-0.434	0.584	-0.740	0.457	-1.579	0.710
IE0	0.520	0.169	3.070	0.002	0.188	0.851
IS0	-0.318	0.310	-1.020	0.306	-0.926	0.291
ITC	-1.231	0.171	-7.190	0.000	-1.566	-0.895
ITF	-1.195	0.293	-4.070	0.000	-1.769	-0.620
ITH	-1.339	0.189	-7.090	0.000	-1.709	-0.969
ITI	-1.648	0.277	-5.950	0.000	-2.191	-1.105
LT0	-0.588	0.487	-1.210	0.227	-1.542	0.367
LU0	0.546	0.650	0.840	0.401	-0.728	1.821
NL1	-0.858	0.522	-1.640	0.100	-1.881	0.165
NL2	-0.342	0.227	-1.500	0.133	-0.788	0.104
NL3	0.071	0.172	0.410	0.681	-0.266	0.407
NL4	-0.061	0.203	-0.300	0.766	-0.459	0.338
NO0	-0.217	0.149	-1.450	0.146	-0.508	0.075

PL9	-1.371	0.514	-2.670	0.008	-2.378	-0.364
PT1	-0.656	0.227	-2.900	0.004	-1.100	-0.212
SE1	0.036	0.152	0.240	0.813	-0.261	0.333
SE2	0.102	0.154	0.660	0.509	-0.200	0.403
SE3	0.022	0.214	0.100	0.919	-0.397	0.441
SI0	-1.094	0.346	-3.160	0.002	-1.773	-0.416
UKC	0.393	0.223	1.760	0.078	-0.043	0.830
UKD	0.287	0.167	1.720	0.085	-0.040	0.615
UKE	-0.042	0.190	-0.220	0.824	-0.414	0.329
UKF	-0.174	0.186	-0.940	0.349	-0.539	0.191
UKG	0.044	0.179	0.250	0.805	-0.308	0.396
UKH	0.218	0.153	1.420	0.155	-0.082	0.517
UKI	0.577	0.145	3.970	0.000	0.292	0.861
UKJ	0.106	0.149	0.710	0.480	-0.187	0.398
UKK	-0.487	0.207	-2.350	0.019	-0.894	-0.081
UKL	0.438	0.196	2.230	0.026	0.053	0.822
UKM	0.593	0.158	3.750	0.000	0.283	0.903
UKN	-0.120	0.316	-0.380	0.705	-0.739	0.499
Company size						
Medium	0.107	0.043	2.480	0.013	0.022	0.192
Small company	-0.219	0.047	-4.630	0.000	-0.312	-0.127
Very large	0.329	0.074	4.450	0.000	0.184	0.474
SIC code						
8	0.346	0.935	0.370	0.711	-1.486	2.178
10	0.451	0.812	0.560	0.578	-1.140	2.043
13	-1.130	0.493	-2.290	0.022	-2.096	-0.164
15	-1.424	0.519	-2.740	0.006	-2.441	-0.406
16	-0.175	0.351	-0.500	0.617	-0.862	0.512
17	-1.377	0.345	-4.000	0.000	-2.053	-0.702
20	-0.273	0.315	-0.870	0.386	-0.890	0.344
22	-1.141	0.454	-2.510	0.012	-2.031	-0.251
24	-0.266	0.344	-0.770	0.440	-0.940	0.408
25	-1.117	0.537	-2.080	0.037	-2.169	-0.065
26	-1.536	0.509	-3.020	0.003	-2.533	-0.539
27	-0.943	0.352	-2.680	0.007	-1.634	-0.253
28	0.911	0.273	3.340	0.001	0.376	1.446
29	0.900	0.508	1.770	0.076	-0.095	1.896
30	-1.039	0.321	-3.230	0.001	-1.669	-0.409
31	0.185	0.772	0.240	0.810	-1.328	1.698
32	-0.625	0.320	-1.960	0.050	-1.251	0.001
33	-0.301	0.318	-0.950	0.343	-0.924	0.322
34	-1.010	0.293	-3.450	0.001	-1.583	-0.436
35	-0.423	0.274	-1.550	0.122	-0.960	0.114
36	0.703	0.272	2.580	0.010	0.169	1.237
37	-0.519	0.298	-1.740	0.082	-1.104	0.065
38	0.739	0.272	2.720	0.007	0.206	1.273
39	-1.085	0.323	-3.350	0.001	-1.718	-0.451
42	-0.997	0.616	-1.620	0.106	-2.205	0.211
47	-1.111	0.532	-2.090	0.037	-2.155	-0.068
48	0.483	0.297	1.630	0.104	-0.099	1.066
49	0.068	0.291	0.230	0.815	-0.503	0.639
50	-1.017	0.282	-3.610	0.000	-1.570	-0.464
51	-1.886	0.388	-4.860	0.000	-2.647	-1.125
54	-0.082	0.476	-0.170	0.863	-1.015	0.851
55	-0.467	0.597	-0.780	0.434	-1.638	0.703
57	-0.552	0.463	-1.190	0.233	-1.459	0.355
59	-0.480	0.313	-1.530	0.126	-1.094	0.134
67	-1.814	0.352	-5.160	0.000	-2.504	-1.125
72	-1.557	0.474	-3.290	0.001	-2.486	-0.628
73	0.065	0.271	0.240	0.809	-0.465	0.596
75	-0.766	0.525	-1.460	0.144	-1.795	0.262
79	-1.085	0.452	-2.400	0.016	-1.971	-0.199
80	-0.190	0.306	-0.620	0.534	-0.790	0.409
82	-0.626	0.440	-1.420	0.155	-1.488	0.236
87	-0.159	0.270	-0.590	0.557	-0.688	0.371
94	1.180	0.883	1.340	0.181	-0.550	2.911
Age	-0.074	0.004	-20.070	0.000	-0.081	-0.066
Constant	-0.361	0.301	-1.200	0.231	-0.951	0.230

Table A.3: Balancing Test Results

This table represents the output of the matched sample. The balancing tests for each matched variable are presented. *Bias (%)* represents the total bias in the sample regarding that specific criteria. The bias is preferred to be lower than 5%. The last column shows the *p*-values of the mean comparison. If p>t is insignificant the mean comparisons between the VC and non-VC-backed group do not significantly differ.

	Mean				t-test
Variable	VC backed	Non VC backed	Bias(%)	t	p>t
Nuts					
AT2	0.002	0.003	-1.4	-0.730	0.468
AT3	0.004	0.005	-1.7	-0.980	0.326
BE1	0.004	0.006	-4.5	-1.110	0.269
BE2	0.022	0.031	-6.1	-1.870	0.061
BE3	0.005	0.005	0.2	0.070	0.945
DE1	0.020	0.014	3.1	1.520	0.128
DE2	0.059	0.069	-4.5	-1.480	0.138
DE3	0.025	0.027	-1.5	-0.440	0.658
DE4	0.013	0.013	-0.4	-0.120	0.901
DE6	0.002	0.003	-1.0	-0.450	0.652
DE7	0.006	0.007	-0.5	-0.230	0.817
DE8	0.003	0.002	1.2	0.480	0.635
DE9	0.007	0.008	-0.8	-0.330	0.738
DEA	0.037	0.032	2.2	0.880	0.380
DEB	0.003	0.003	0.0	0.000	1.000
DEC	0.003	0.005	-3.6	-1.030	0.304
DED	0.015	0.015	-0.1	-0.040	0.969
DEE	0.003	0.004	-2.5	-0.940	0.345
DEF	0.002	0.003	-0.4	-0.190	0.851
DEG	0.009	0.007	1.7	0.580	0.562
DK0	0.055	0.059	-1.8	-0.590	0.557
EE0	0.000	0.000	0.6	0.580	0.564
ES1	0.001	0.001	0.2	0.170	0.862
ES2	0.008	0.007	0.5	0.220	0.830
ES3	0.004	0.005	-1.7	-0.760	0.450
ES4	0.002	0.001	2.6	1.270	0.204
ES5	0.014	0.011	2.0	0.890	0.375
ES6	0.002	0.003	-1.1	-0.490	0.625
FI1	0.048	0.044	2.0	0.650	0.514
FR1	0.059	0.059	0.0	0.000	1.000
FRB	0.001	0.000	2.2	1.220	0.223
FRC	0.003	0.002	2.5	0.830	0.405
FRD	0.004	0.005	-1.0	-0.280	0.782
FRE	0.007	0.006	1.1	0.340	0.731
FRF	0.007	0.007	-0.2	-0.060	0.956
FRG	0.005	0.005	1.0	0.340	0.735
FRH	0.008	0.007	0.6	0.160	0.869
FRI	0.007	0.005	3.4	1.100	0.272
FRJ	0.014	0.010	4.1	1.250	0.211
FRK	0.032	0.034	-1.1	-0.320	0.752
FRL	0.017	0.020	-2.9	-0.810	0.419
HU1	0.001	0.001	-0.3	-0.160	0.873
HU2	0.000	0.001	-0.5	-0.220	0.827
IE0	0.027	0.025	1.7	0.500	0.615
IS0	0.002	0.003	-2.4	-0.750	0.453
ITC	0.008	0.010	-1.3	-0.960	0.339
ITF	0.001	0.001	-0.3	-0.260	0.796
ITH	0.005	0.008	-1.8	-1.470	0.142
ITI	0.001	0.001	0.0	0.000	1.000
LT0	0.001	0.001	0.8	0.370	0.715
LU0	0.000	0.001	-5.2	-1.120	0.262
NL1	0.000	0.000	0.0	0.000	1.000
NL2	0.004	0.003	1.2	0.640	0.521
NL3	0.017	0.018	-0.9	-0.320	0.746
NL4	0.007	0.005	2.7	1.230	0.217
NO0	0.029	0.023	3.2	1.280	0.202
PL9	0.000	0.001	-0.3	-0.220	0.827
PT1	0.004	0.003	0.8	0.390	0.697
SE1	0.033	0.027	3.6	1.240	0.215
SE2	0.029	0.027	1.1	0.370	0.712
SE3	0.006	0.004	2.7	1.080	0.282
SI0	0.001	0.001	-0.4	-0.310	0.758
UKC	0.008	0.010	-1.7	-0.500	0.619
UKD	0.021	0.022	-1.0	-0.320	0.747
UKE	0.010	0.009	0.7	0.250	0.806
UKF	0.010	0.010	-0.3	-0.100	0.924

UKG	0.014	0.014	0.5	0.160	0.873
UKH	0.033	0.038	-3.4	-1.040	0.297
UKI	0.070	0.068	0.8	0.220	0.824
UKJ	0.041	0.036	2.6	0.880	0.380
UKK	0.006	0.005	1.0	0.430	0.668
UKL	0.013	0.016	-3.2	-0.900	0.368
UKM	0.039	0.040	-0.6	-0.170	0.865
UKN	0.002	0.001	1.6	0.710	0.479
Company size					
Medium	0.491	0.460	6.2	2.190	0.029
Small company	0.284	0.294	-2.3	-0.830	0.406
Very large	0.070	0.080	-4.2	-1.290	0.198
	0.000	0.001	-1.7	-0.410	0.683
SIC code					
8					
10	0.000	0.000	2.2	1.000	0.317
13	0.000	0.001	-0.3	-0.220	0.827
15	0.000	0.000	0.7	1.000	0.317
16	0.004	0.004	-1.3	-0.450	0.654
17	0.002	0.002	-0.1	-0.120	0.908
20	0.006	0.005	0.9	0.380	0.705
22	0.001	0.001	0.0	0.000	1.000
24	0.003	0.003	0.6	0.260	0.796
25	0.000	0.000	0.2	0.260	0.796
26	0.000	0.001	-0.2	-0.220	0.827
27	0.002	0.001	1.3	0.750	0.453
28	0.136	0.156	-7.2	-1.970	0.049
29	0.002	0.002	-1.3	-0.330	0.739
30	0.003	0.003	0.1	0.090	0.928
31	0.000	0.001	-2.0	-0.580	0.564
32	0.004	0.002	2.2	1.210	0.225
33	0.005	0.006	-1.9	-0.760	0.449
34	0.007	0.006	0.6	0.460	0.643
35	0.045	0.046	-0.6	-0.270	0.786
36	0.158	0.147	3.5	1.020	0.307
37	0.008	0.008	0.0	0.000	1.000
38	0.168	0.153	5.1	1.510	0.130
39	0.003	0.003	-0.7	-0.420	0.673
42	0.000	0.000	0.4	0.260	0.796
47	0.000	0.000	0.0	0.000	1.000
48	0.021	0.024	-2.8	-0.760	0.445
49	0.016	0.017	-0.6	-0.190	0.853
50	0.012	0.011	0.4	0.300	0.761
51	0.001	0.001	0.2	0.370	0.715
54	0.002	0.001	2.5	0.980	0.327
55	0.000	0.000	1	0.580	0.564
57	0.001	0.001	-0.6	-0.310	0.758
59	0.006	0.004	1.8	0.820	0.413
67	0.001	0.001	-0.1	-0.130	0.895
72	0.000	0.001	-0.2	-0.220	0.827
73	0.193	0.194	-0.3	-0.100	0.924
75	0.001	0.001	0.0	0.000	1.000
79	0.001	0.001	0.3	0.170	0.862
80	0.008	0.007	1.2	0.440	0.661
82	0.001	0.001	0.8	0.450	0.655
87	0.174	0.182	-2.0	-0.710	0.476
94	0.000	0.001	-2.6	-0.580	0.564
Age	5.220	5.240	-0.5	-0.170	0.862

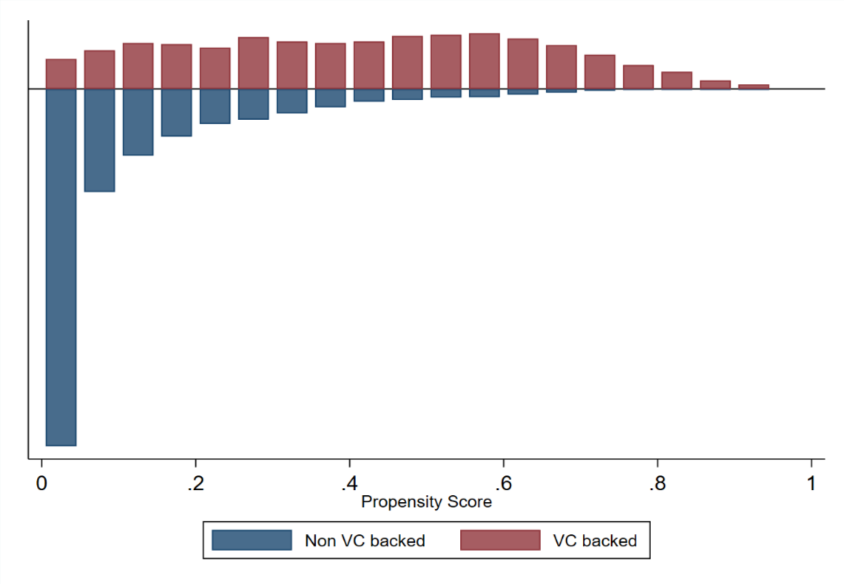

Figure A.1: Unmatched Sample
This figure represents the sample overlap based on the propensity score analysis before matching, corresponding results in table A.2

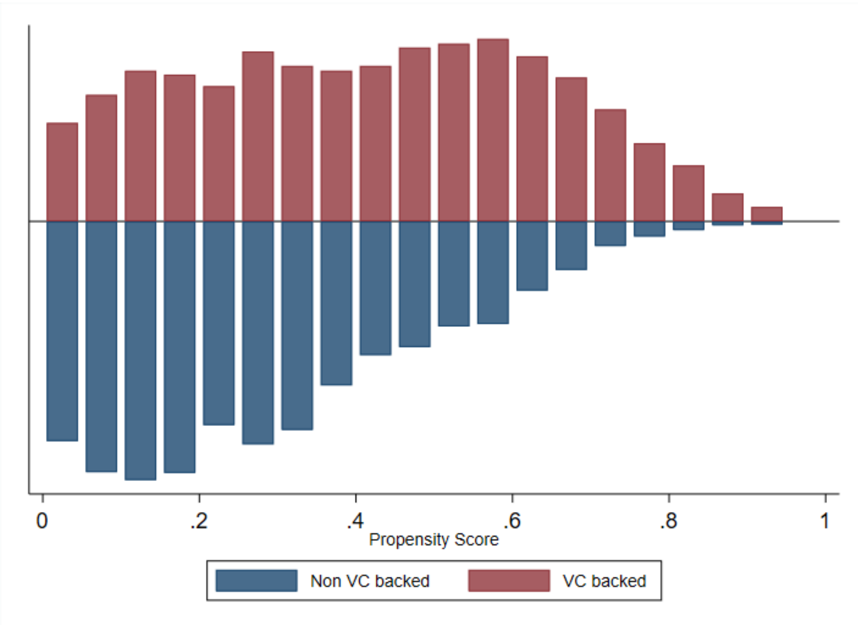

Figure A.2: Matched Sample
This figure represents the sample overlap based on the propensity score analysis after matching, corresponding results in table A.3

Table A.4: Industries

Sample distribution among main industries

	Non-VC-backed	VC-backed	Total
Agriculture, forestry and fishing	7	7	14
Mining & Construction	27	16	43
Manufacturing industries	1376	1384	2760
Transportation communication, electric, gas and sanitary service	102	94	196
Trade (wholesale & retail)	105	54	159
Finance, insurance real estate	10	3	13
Services	1413	948	2361
Public administration	1	1	2
Total	3041	2507	5548

Table A.5: Correlation Matrix

This table reports the Pairwise correlations

Variables	(1)	(2)	(3)	(4)
(1) Patents	1.000			
(2) Citations / Patents	0.458	1.000		
(3) Age	0.364	0.170	1.000	
(4) Syndicate size	0.301	0.161	0.130	1.000

Table A.6: Hausman Tests

Innovation measured as patents for 5 year after investment period analyses

	GVC vs. non-VC-backed	GVC vs. PVC	GVC vs. CVC	Homogenous vs. heterogenous
Chi-square test value	125.33	181.71	59.02	346.50
P-value	0.000	0.000	0.000	0.000

Innovation measured as citation weighted patents and 5 years after investment

	GVC vs. non-VC-backed	GVC vs. PVC	GVC vs. CVC	Homogenous vs. heterogenous
Chi-square test value	101.73	55.64	50.01	85.71
P-value	0.000	0.000	0.000	0.000

Table A.7: Robustness Fixed Effects Analyses on Patents Without the UK

The table displays the robustness analysis for excluding the UK from the sample. The results of the fixed effects panel regressions are displayed in column 1-4 for each subsample 5 years after the investment. Each panel is constructed around a unique VC investment in a company or a non-VC-backed company. Dependent variable represents the patents of a company at time *t*. *After* is a dummy variable representing whether the period occurs after the investment. *After*GVC* represents the interaction between the after period and GVC investments. *After*Homogenous* represents the interaction between homogenous investments and the after period. *Age* represents the age of a company since incorporation. *Syndicate size* represents the number of co-investors. Year dummies are added to control for the observational year. Robust standard errors are used and reported in parentheses. ***, **, *, represent the statistical significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)
	GVC vs. Non-VC-backed	GVC vs. PVC	GVC vs. CVC	Homogenous vs. Heterogenous
After	0.002	0.111***	0.157***	0.147***
	(0.013)	(0.024)	(0.049)	(0.055)
*After*GVC*	0.226***	-0.080*	-0.099*	
	(0.037)	(0.042)	(0.059)	
*After*Homogenous*				-0.088*
				(0.053)
Age	0.061**	0.327***	0.378***	0.336***
	(0.024)	(0.030)	(0.043)	(0.024)
Syndicate size		0.090	-0.029	0.090*
		(0.056)	(0.132)	(0.046)
Year dummies	Yes	Yes	Yes	Yes
Constant	0.208***	-0.403***	-0.393***	-0.389***
	(0.020)	(0.078)	(0.134)	(0.061)
Observations	25,188	10,446	4,335	17,479
R-squared	0.552	0.625	0.620	0.640
Adjusted R-squared	0.551	0.624	0.618	0.639
VC groups	2,600	1,109	474	1,838
F-Value	565.57***	172.84***	77.20***	293.83***

Table A.8: Robustness Fixed Effects Analyses on Citation Weighted Patents Without the UK

The table displays the robustness analysis for excluding the UK from the sample. The results of the fixed effects panel regressions are displayed in column 1-4 for each subsample 5 years after the investment. Each panel represents a unique VC investment in a company or a non-VC-backed company. Dependent variable represents the citation weighted patents of a company at time *t*. *After* is a dummy variable representing whether the period occurs after the investment. *After*GVC* represents the interaction between the after period and GVC investments. *After*Homogenous* represents the interaction between homogenous investments and the after period. *Age* represents the age of a company since incorporation. *Syndicate size* represents the number of co-investors. Year dummies are added to control for the observational year. Robust standard errors are used and reported in parentheses. ***, **, *, represent the statistical significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)
	GVC vs. Non-VC-backed	GVC vs. PVC	GVC vs. CVC	Homogenous vs. Heterogenous
After	0.041***	-0.002	0.001	0.069
	(0.010)	(0.019)	(0.038)	(0.045)
*After*GVC*	0.135***	0.087**	0.073	
	(0.036)	(0.039)	(0.051)	
*After*Homogenous*				-0.035
				(0.042)
Age	0.022	0.249***	0.199***	0.231***
	(0.021)	(0.026)	(0.040)	(0.021)
Syndicate size		0.030	0.013	-0.001
		(0.044)	(0.093)	(0.038)
Year dummies	Yes	Yes	Yes	Yes
Constant	0.099***	-0.058	0.048	0.027
	(0.019)	(0.091)	(0.101)	(0.066)
Observations	25,188	10,446	4,335	17,479
R-squared	0.140	0.186	0.230	0.183
Adjusted R-squared	0.139	0.185	0.226	0.182
VC groups	2,600	1,109	474	1,838
F-value	66.37***	23.73***	13.10***	39.83***

Table A.9: Robustness Fixed Effects Analyses on Patents Without Dominant Industries

The table displays the robustness analyses for excluding the industries with sic codes 28, 36, 38, 73 and 87 from the sample. The results of the fixed effects panel regressions are displayed in column 1-4 for each subsample 5 years after the investment. Each panel represents a unique VC investment in a company or a non-VC-backed company. Dependent variable represents the patents of a company at time *t*. *After* is a dummy variable representing whether the period occurs after the investment. *After*GVC* represents the interaction between the after period and GVC investments. *After*Homogenous* represents the interaction between homogenous investments and the after period. *Age* represents the age of a company since incorporation. *Syndicate size* represents the number of co-investors. Year dummies are added to control for the observational year. Robust standard errors are used and reported in parentheses. ***, **, *, represent the statistical significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)
	GVC vs. Non-VC-backed	GVC vs. PVC	GVC vs. CVC	Homogenous vs. Heterogenous
After	-0.021	0.132**	0.255**	0.213
	(0.031)	(0.055)	(0.125)	(0.143)
*After*GVC*	0.200**	-0.059	-0.191	
	(0.094)	(0.103)	(0.148)	
*After*Homogenous*				-0.132
				(0.141)
Age	0.130***	0.312***	0.486***	0.312***
	(0.045)	(0.066)	(0.101)	(0.0569)
Syndicate size		-0.046	-0.441	0.004
		(0.144)	(0.441)	(0.121)
Year dummies	Yes	Yes	Yes	Yes
Constant	0.107***	-0.390*	0.394	-0.276*
	(0.039)	(0.203)	(0.284)	(0.163)
Observations	5,416	1,953	763	3,020
R-squared	0.509	0.578	0.591	0.590
Adjusted R-squared	0.508	0.573	0.580	0.587
VC groups	559	206	80	316
F-value	122.69***	29.54***	13.71***	45.23***

Table A.10: Robustness Fixed Effects Analyses on Citation Weighted Patents Without Dominant Industries

The table displays the robustness analyses for excluding the industries with sic codes 28, 36, 38, 73 and 87 from the sample. The results of the fixed effects panel regressions are displayed in column 1-4 for each subsample 5 years after the investment. Each panel represents a unique VC investment in a company or a non-VC-backed company. Dependent variable represents the citation weighted patents at time t. *After* is a dummy variable representing whether the period occurs after the investment. *After*GVC* represents the interaction between the after period and GVC investments. *After*Homogenous* represents the interaction between homogenous investments and the after period. *Age* represents the age of a company since incorporation. *Syndicate size* represents the number of co-investors. Year dummies are added to control for the observational year. Robust standard errors are used and reported in parentheses. ***, **, *, represent the statistical significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)
	GVC vs. Non-VC-backed	GVC vs. PVC	GVC vs. CVC	Homogenous vs. Heterogenous
After	0.047**	0.057	0.035	0.065
	(0.019)	(0.041)	(0.093)	(0.122)
*After*GVC*	0.185	0.080	0.042	
	(0.113)	(0.118)	(0.146)	
*After*Homogenous*				0.002
				(0.115)
Age	-0.049	0.206***	0.167	0.188***
	(0.053)	(0.067)	(0.141)	(0.053)
Syndicate size		0.021	-0.025	0.023
		(0.118)	(0.270)	(0.096)
Year dummies	Yes	Yes	Yes	Yes
Constant	0.130***	-0.007	0.355***	0.067
	(0.040)	(0.094)	(0.064)	(0.071)
Observations	5,416	1,953	763	3,020
R-squared	0.110	0.181	0.189	0.183
Adjusted R-squared	0.107	0.173	0.166	0.177
VC groups	559	206	80	316
F-value	10.77***	5.78***	3.00***	8.77***