Does Governmental Venture Capital Spur Innovation? - A comparison with private venture capital in Sweden

Master's Thesis 30 credits
Programme: Master's Programme in Accounting and Financial Management
Specialisation: Financial Accounting and Management control
Department of Business Studies
Uppsala University
Spring Semester of 2021
Date of Submission: 2021-06-01

Yunxin Chang
Dennis Astorsdotter

Supervisor: David Andersson

Acknowledgements

First of all, we want to thank our supervisor David Andersson for all the support, good comments, solid arguments and everything he taught us while working on this thesis. We would also like to thank SVCA for providing the data that made this study possible. Finally, we thank our opponents, proofreaders, and all members of our seminar group for all the valuable comments, time and energy you spent on helping us improve our thesis.

Uppsala, 28 May, 2021 *Yunxin Chang, Dennis Astorsdotter*

Abstract

Governments have increased their commitment to spur innovation by increasing the amount of venture capital (VC) flowing to the venture capital market over the last decades. Still, research shows that governmental venture capital (GVC) has no impact on innovation. The literature comparing governmental and private venture capital's effect on innovation is scarce. Therefore, this study explores how different types of VC affects innovation in Swedish entrepreneurial companies. Based on VC data from the Swedish Venture Capital Association (SVCA), we use 440 VC-backed companies and 440 control companies to test the effects of governmental venture capital, private venture capital (PVC), and mixed venture capital (MVC, a combination of GVC and PVC) on four innovation indicators - patent grants, passive citations, trademarks, and industrial design rights. We use fixed-effects models to compare different VC types and Difference-in-Differences models to draw inferences about causality. Our findings show that all types of venture capital positively affect innovation, while MVC has the most substantial effects. PVC spur innovation mainly through trademarks, while GVC increases both trademarks and patent quality. We argue that MVC has access to an immense amount of capital and can allocate its non-financial resources better than both PVC and GVC separately. We also suggest that GVC focuses more on innovation quality and PVC focuses more on commercializing innovations and bringing them to the market.

Keywords: Innovation, Patent, Design, Trademark, Venture capital, Private venture capital, Governmental venture capital, Mixed venture capital, Comparison

Contents

1 Introduction

Innovation is widely known as a vital source of economic growth and job creation. It is well acknowledged that entrepreneurial companies make substantial contributions to innovation (Audretsch & Thurik 1999, Wong et al. 2005, Cumming & Johan 2016). Therefore, to promote innovation, governments have increased the amount of venture capital (VC) flowing to entrepreneurial companies in the last three decades (Bottazzi & Da Rin 2002, Arque-Castells 2012, Leleux & Surlemont 2003). In 2009, governmental venture capital (GVC) became the most common VC type in Europe (EVCA 2014). Since a substantial amount of taxpayers' money is allocated to support innovation, it is essential that GVC use their resources effectively and supports innovation successfully. But research shows that GVC does not affect innovation in GVC-backed companies (Bertoni & Tykvova 2015). Apart from Bertoni & Tykvova (2015), there is little empirical evidence on how GVC affects innovation in entrepreneurial companies compared to private venture capital (PVC) and mixed venture capital (MVC) [1].

VC funds' services as financial intermediaries and is designed to supply capital and limit the risks with investments in new ventures or business expansions (Law 2018). Thus VC can provide financial support for young entrepreneurial companies. One of the most considerable obstacles for entrepreneurial companies is getting funded (Hall & Lerner 2010, Beck & Demirguc-Kunt 2006). Although entrepreneurial companies, as an aggregate, are expected to provide a large return in the long term, they are associated with substantial risk (Schultz 2011, Berger 2014). Four major risk factors are lack of internal cash flow, lack of collateral for external debt financing, information asymmetries between firms and potential investors, and agency problems, which can lead to high monitoring costs, making investments less attractive (Carpenter & Petersen 2002). To manage these risks, entrepreneurial companies often resort to venture (equity) capital, which can reduce, or eliminate, financial constraints on entrepreneurial companies (Caliendo & Kopeinig 2008, Jeng & Wells 2000, Leland & Pyle 1977, Chan 1983).

In general, VC is commonly divided into PVC and GVC, which have significantly different objectives (Leleux & Surlemont 2003). PVC funds are commonly organized as a form of limited partnership with a predetermined lifespan for their investments, commonly ten years (Sahlman 1990). The limited lifespan of investments, combined with PVC funds' nature of seeking profit, puts pressure on PVC funds to target investments that generate quick returns (Arque-Castells 2012, Luukkonen et al. 2013, Svensson 2011). In contrast, GVC funds operate to mitigate welfare losses by investing in areas where there is sys-

[1] MVC investments are defined by investments made simultaneously by PVC funds and GVC funds in the same companies.

tematic underinvestment, with the intent to spur innovation, job creation, and economic growth (Lerner 2002, Svensson 2011, European Court of Auditors 2019, Bertoni et al. 2019). Therefore, GVC funds should allocate capital to early-stage entrepreneurial companies with high growth and innovative potential (Colombo et al. 2016, Lerner 1999, Greene et al. 2001). Because of agency problems, there is a risk that PVC funds' general managers are pressured to focus on short-term returns, while GVC funds' general managers' focus should be more long-term. Because of PVC and GVC funds' different objectives, we can expect differences in investment selection, nurturing, and monitoring – and in turn, expect different impacts on innovation.

Previous work has found that PVC can spur innovation. For example, Kortum & Lerner (2000) show that increased VC activity is associated with significantly higher innovation rates in a US-setting during 1965-1992[2]. However, this study uses a dataset before the substantial increases in GVC, and there are concerns that governments increased involvement are crowding out PVC (Armour & Cumming 2006, Cumming & MacIntosh 2006). Furthermore, Ueda & Hirukawa (2008) have raised concerns about reverse-causality – that VC funds select already innovative firms rather than spur innovation in these firms. The literature on how GVC affect innovation is sparse. Though more work is needed, there is evidence that PVC spurs more innovation than GVC and that GVC is no better at spurring innovation than companies that do not receive VC (Bertoni & Tykvova 2015). Therefore there is a need to further examine governments' increased involvement in the VC market and their effects on innovation.

This study aims to expand on previous work by focusing on a Swedish setting. Research on how different types of VC investors affect innovation is scarce, even though Dutta et al. (2017) has found that Sweden is one of the most innovative countries in the world. Therefore, we define our research question: *How do different types of VC investors affect innovation in Sweden?* Regarding VC background in Sweden, the first Swedish GVC fund was founded in 1970[3] (Tillväxtanalys 2017). Since then, Swedish GVC has grown to consistently account for around 25% of the Swedish VC market (Tillväxtanalys 2020). Swedish GVC funds' primary goal is to mitigate welfare losses by supporting innovative, entrepreneurial companies in the early stages. However, the Swedish National Audit Office (Riksrevisionen 2014) presents a reality where Swedish GVC funds instead focus on a few geographical areas and selected economic sectors (Riksrevisionen 2014). The

[2] Historically PVC was the only type of VC. Therefore, when early studies refer to VC, it should in general be interpreted as PVC.

[3] The fund was called Svetab. Technically, Sveriges investeringsbank invested in private companies as early as 1967 but is not usually counted as a GVC fund because it focused on dept capital and was not structured as a fund. In 1979, the Industrifonden foundation was formed, which is still one of the leading GVC players.

review by Riksrevisionen (2014) also indicates that Swedish GVC funds' have crowded out Swedish PVC to some extent.

The purpose of this study is to examine how different types of VC (PVC, GVC, and MVC) affect innovation in Swedish entrepreneurial companies. To conduct the study, we focus on the relationship between two variables. Our independent variable is *VC type*, and our dependent variable is *innovation*. As for the type of VC, we divide VC investors into three different categories: private venture capital (PVC), governmental venture capital (GVC), and mixed venture capital (MVC). As for the dependent variable, to capture several dimensions of innovation, we include several proxies: patent grants, patent citations, trademark rights, and industrial design rights. This study follows a quasi-experimental design, using an observational data sample of VC investments from 2004 to 2014, structured as panel data. We use a fixed-effects regression model to test different impacts on innovation between different VC investors and a difference-in-differences model to draw inferences on causality.

Our findings show that receiving VC have positive and significant effects on innovation, no matter what type of VC. The results also show that receiving MVC have substantial effects on patent grants, patent quality, and trademark rights. Comparing GVC and PVC, both types significantly and positively affect trademarks, but the impact on trademarks are more potent for PVC. GVC-backed companies display significantly higher patent quality than PVC-backed and non-VC-backed companies (the control group). Thus, PVC results in more trademark rights than GVC, but GVC produces higher quality patents than PVC. Furthermore, the evidence shows that entrepreneurial companies receiving MVC have the highest overall level of innovation.

This study contributes to two branches of literature. First, it provides new knowledge to the literature on innovation by identifying which VC investors contribute to innovation. Second, the results contribute to the VC literature by better understanding the different advantages of different VC types and how their specific characteristics influence innovation in entrepreneurial companies in Sweden. In a practical sense, our findings support policymakers when formulating or revising policies regarding Sweden's innovative environment.

The rest of this paper is structured as follows. In the second section, relevant theories are scrutinized to construct four hypotheses. In the third section, data and methods are presented. In the fourth section, we present the results. In the fifth section, we discuss the results based on our four hypotheses. In the sixth section, we present our conclusions, discuss the limitations of this study and make suggestions for further work.

2 Theoretical framework and hypothesis development

To remove financial constraints, entrepreneurial companies can seek funding from various sources, such as debt funding, equity funding, and internal funding. A systematic overview of available financial sources for entrepreneurial companies is presented in Figure 1. Entrepreneurial companies have difficulty obtaining debt financing because of their associated high risks; therefore, equity funding is often their best alternative (Hall & Lerner 2010). As shown in Figure 1, venture capital is a type of private equity (equity in non-listed companies), as opposed to public equity, that refers to equity in listed companies. As for the difference between venture capital funds and business angels, business angels are often individuals who only invest their own money, whereas venture capitalists professionally manage pooled capital of others in a VC fund. When we mention "venture capital" (VC) in this study, we mean it as non-specific/venture capital in general, including both PVC and GVC, as shown in Figure 1. In the last level, we separate PVC and GVC. What is not addressed in Figure 1 is MVC investments, which is when PVC funds and GVC funds invest directly in the same portfolio company.

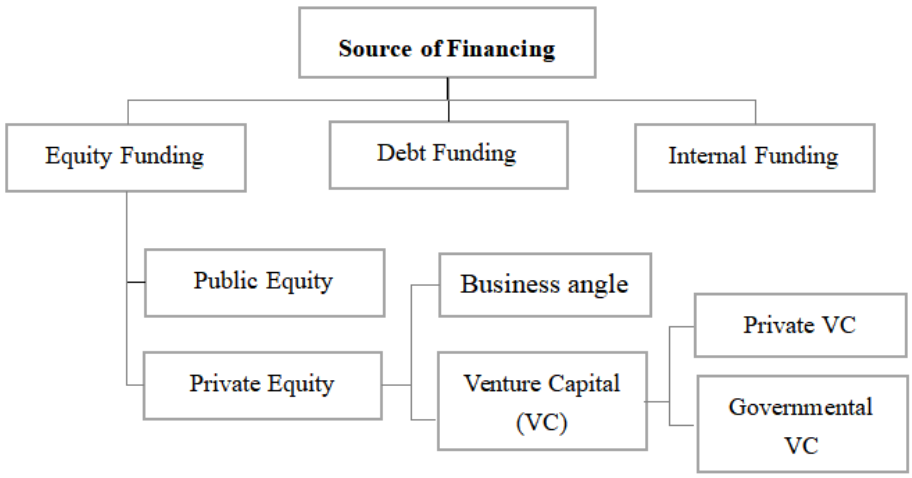


FIGURE 1. Source of financing for entrepreneurial companies

2.1 Venture capital and innovation

VC funds are explicitly designed to channel funds and handle the high risks associated with investments in entrepreneurial companies. VC funds limited partners (capital suppliers) accept the high risks, but in return, they expect a high growth rate, often driven by the companies inventions and innovations (Carpenter & Petersen 2002).

VC investments both mitigate the financial gap and provide valuable guidance to entrepreneurial companies (Lin et al. 2019). VC investments have also been shown to have positive effects on innovation in many different studies. VC-backed entrepreneurial companies have a significantly lower default rate than other entrepreneurial companies (Dorsey 1979, Davis & Stetson 1985). Assuming that companies that do not default are more likely to contribute to innovation, this shows that VC can spur innovation. Besides, increases in VC activity have been shown to lead to substantial increases in patented innovations in the US (Kortum & Lerner 2000) and Germany (Tykvova 2000). Furthermore, increases in VC activity can lead to substantial increases in new business creation (Popov & Roosenboom 2013). VC-backed firms have also been shown to grow faster (Sahlman 1990, Suzuki 1996, Hellmann & Puri 2000, Engel 2002, Hall 2002) and bring new products to the market faster and at a higher pace than non-VC-backed firms (Hellmann & Puri 2000).

Hirukawa & Ueda (2011) question the causality of previous work and find evidence of reverse causality; that innovative firms attract venture capital rather than venture capital spurring innovation in portfolio firms. However, Bertoni & Tykvova (2015) show that PVC and MVC spur innovation more than their non-VC-backed counterparts, even after controlling for reverse causality.

To sum up, the evidence shows that venture capital both prefers and rewards innovative companies by selecting them for funding. VC funds also act as a catalyst for innovation by removing capital constraints. Thereby, VC-backed firms are likely to produce more innovation than their non-VC-backed counterparts during any given period. Therefore, our first hypothesis is that:

H1: VC has a positive impact on innovation

2.2 Type of venture capital investor

In this study, we separate the type of VC into three categories: private venture capital (PVC), governmental venture capital (GVC), and mixed venture capital (MVC). MVC investments refer to direct investments from both PVC and GVC in the same portfolio company. It is essential to understand what separates different VC types – their different objectives and their differences in financial and non-financial resources. Non-financial resources refer to the VC funds' general managers' level of knowledge and experience in investment selection, nurturing, guidance, and monitoring of their portfolio companies.

An overview of the differences between PVC and GVC is presented in Table 1.

TABLE 1: OVERVIEW OF PRIVATE AND GOVERNMENTAL VENTURE CAPITAL

	PVC	GVC
Source of capital	Private institutions and wealthy families or individuals	The government (taxpayers)
Objectives	To earn a high and quick return	Mitigating welfare losses by investing in innovation
Level of risk aversion	Risk-averse	Risk-tolerant
Investment targets	Late-stage entrepreneurial companies	Early-stage entrepreneurial companies
Non-financial resources	Skilled, experienced with a large network of experts, high incentives, few and large investments	Lacking in knowledge and experience, low incentives, many and small investments

Notes: MVC is not included in this table because it simply shares the features of both GVC and PVC.

2.2.1 PVC and innovation

PVC funds' source of capital is private institutions and wealthy families or individuals. PVC funds are typically structured as limited partnerships, where the fund's general partners invest and manage capital raised from its limited partners (Sahlman 1990, Litvak 2009). The general partners are expected to add value to the limited partners through capital allocation and a high engagement level (de Carvalho et al. 2008). Their primary objective is commonly to earn a high and quick return (Leleux & Surlemont 2003). PVC funds tend to prefer late-stage investments that allow them to exploit short-term returns (Ibid.). They are interested in innovation because innovation signals value as it is generally accepted as the key source of firm growth (Coad & Rao 2008). Furthermore, innovation has been identified as a source of premium returns in the event of an IPO (Deeds et al. 1997). PVC accounts for approximately 75% of all VC investment in Sweden (Tillväxtanalys 2020).

Previous studies reveal that PVC funds usually perform better than GVC funds. The explanation can be categorized into two categories. First, PVC funds have been shown to be better at addressing the agency problem (Cumming & Johan 2013, Gompers & Lerner 2004, Cumming et al. 2017). A particular remuneration clause for fund managers can provide a great incentive to maximize investment returns and make them prefer late-stage investments that are less risky. This term usually gives PVC fund managers a fixed salary based on invested capital and a contingent fee based on the fund's profits. However, it also includes a punishing fee in case of poor performance (Gompers & Lerner 1999, Jääskeläinen et al. 2007, Cumming et al. 2017). In contrast, GVC funds' are established without private contractual clauses, so agency problems are more significant and more expensive (Cumming et al. 2017). However, GVC fund managers generally have fixed salaries and thus have smaller incentives to maximize profits.

Second, PVC fund managers provide better non-financial resources than GVC fund managers (de Carvalho et al. 2008, Bertoni & Tykvova 2015, Tykvová & Walz 2007, Cumming et al. 2017). Early studies have shown that PVC funds are active in their portfolio companies, they opt for positions on the board, provide guidance, monitor operations, plan future funding, make strategic analysis and so on (Sahlman 1990, Gorman & Sahlman 1989, Sapienza & Gupta 1994). By active involvement, PVC managers can access internal information that mitigates adverse selection and moral hazard problems (Sahlman 1990, Repullo & Suarez 2000). Thus PVC plays a prominent role in the corporate governance of the portfolio companies (Tykvova 2006). In addition, Hellmann & Puri (2000) found that PVC managers are better at commercialization, i.e., bringing innovative products to market at the right time. Furthermore, PVC draws on their extensive networks to hire crucial senior managers and expert staff, who are essential for the growth of entrepreneurial companies (de Carvalho et al. 2008). In contrast, GVC managers are less involved in non-financial activities (Vanacker et al. 2013, Schäfer & Schilder 2006).

To sum up, previous studies have found that problems with agency costs, adverse selection, and moral hazard are better mitigated in PVC-backed companies than in GVC-backed companies. Furthermore, it has been found that PVC managers are more active in their portfolio companies and provide superior non-financial resources to the ones provided by GVC managers. Thus the following hypothesis is made:

H2: Private venture capital is more effective than governmental venture capital in supporting innovation

2.2.2 GVC and innovation

The source of GVC capital is taxpayers' money. GVC funds' objective is always to spur innovation to mitigate welfare losses (Bertoni & Tykvova 2015). Swedish GVC funds are structured as limited companies with an explicit goal to support areas with systematic underinvestment and invest in early-stage companies (Riksrevisionen 2014). Early-stage companies commonly appear unattractive to PVC funds general manages' because of their associated high risks (Bertoni et al. 2015, Colombo et al. 2016, Greene et al. 2001, Svensson 2011), or expected low returns. In contrast to their explicit aims, previous findings suggest that GVC does not spur innovation (Bertoni & Tykvova 2015). Furthermore, Swedish GVC funds lack the necessary knowledge and skills to support their portfolio companies (Parliamentary Audit Office 1996) and are unsuccessful in allocating financial resources to early-stage companies (Riksrevisionen 2014). Swedish GVC systematically accounts for approximately 25% of the Swedish VC market (Tillväxtanalys 2020).

There are three theories for why GVC is needed: spillover effects, underinvestment in early-stage companies, and asymmetric information. First, the incentive for private investors to invest in innovation is considered too weak. Because the innovative company is unlikely to get exclusive rights to all of its inventions, some of its investment in innovation will likely generate new inventions in other companies – called spillovers (Jaffe & Jaffe 1996). Thus, private investors will likely invest less than what is socio-economically desirable (Arrow 1962). To close this financial gap, GVC funds' should invest in innovation that contributes mainly to social welfare, but where the returns are likely to be low for any private investors.

Second, there is systematic underinvestment in early-stage companies because, as mentioned in the previous section, PVC funds tend to invest in late-stage companies. Early-stage companies are more likely to create groundbreaking innovations (Kerr & Nanda 2015), and it is these groundbreaking, risky investments that have the largest innovative value (Hall & Lerner 2010). By providing early-stage funding, GVC can act as a catalyst for new industries to emerge, resulting in new job creation and more innovation. Once a new industry has been created, there are both experienced workers and legal experience of the industry, which mitigates the risks of further investments (Svensson 2011). Therefore, to facilitate establishing new industries, GVC is needed to fund high-risk, early-stage companies (Gompers et al. 2009). Thus, investments in early-stage companies reduce risk and encourage further investment and increase long-term entrepreneurial and innovative activity (Lerner 2010).

Third, asymmetric information is a problem in the process of investment selection. Because PVC fund managers are relatively risk-averse and therefore prefer late-stage investments, GVC is needed to make investments in companies with potentially high asymmetric information to signal quality and help attract PVC (Carpenter & Petersen 2002) – also called the crowding-in effect (Lerner 1999). Though some evidence supports this crowding-in effect (e.g. Hood 2000, Leleux & Surlemont 2003, Brander et al. 2015), others find evidence of the opposite, a crowding-out effect (e.g. Armour & Cumming 2006, Bertoni et al. 2015, Cumming & MacIntosh 2006, Riksrevisionen 2014). The rationale behind the crowding-out effect is that GVC might be cheaper than PVC if GVC wavers part of the risk premium to pursue other interests, such as job creation and innovation.

As a result, GVC would attract better investments and only leave the “lemons” to PVC, raising entry barriers and crowding out new PVC. For GVC to have a crowding-in effect, GVC should be set up to subsidize the high risks associated with investments in early-stage companies (e.g. by sharing the risks in a MVC investment) (Colombo et al. 2016, Lerner 2002, Svensson 2011, Colombo et al. 2016). Supporting this theory, Bertoni & Tykvova (2015) showed that GVC has a negligible effect on innovation if examined independently but that there will be significant and positive effects on innovation if GVC and PVC invest jointly in a MVC investment.

To sum up, GVC source of capital is taxpayers’ money. Their objective is to mitigate long-term welfare losses. GVC is needed for: investments with potentially high spillover effects, early-stage companies with systematic underinvestment, and to attract PVC by reducing asymmetric information and signal quality. The most significant impact of GVC can be seen when it is set up to subsidize the high risks in early-stage companies, e.g. when GVC is set up to ”match” PVC investments in portfolio companies. The need for GVC funds are clear in theory, but previous studies show that it is not easy to translate the theory into reality. In the worst case, GVC has a crowding-out effect on PVC. Based on previous reports from Sweden and Europe, we formulate the following hypothesis:

H3: There is no difference in the degree of innovation between companies that receive GVC-backing and companies that do not receive any type of VC.

2.2.3 MVC and innovation

We call it mixed venture capital (MVC) when one or more PVC and GVC funds invest directly in the same portfolio company. Note that there are no MVC funds but that MVC always refers to investments.

It has been found that MVC investments can lead to a higher degree of innovation Bertoni & Tykvova (2015). In addition, there are indications that the highest level of performance comes when GVC funds and PVC funds co-invest (Brander et al. 2015). It has also been found that MVC investments have a higher likelihood of facilitating successful exits (IPO or acquisition) (Cumming et al. 2017). The joint proposition is that MVC investments successfully combine the advantages of both PVC and GVC while mitigating the disadvantages of both types of VC (Leleux & Surlemont 2003, Bertoni & Tykvova 2015).

In theory, it does not matter where the financial support comes from; therefore, it is likely that different VC types differ in the use of non-financial resources. Since MVC has been shown to generate more innovation, it has been suggested that non-financial resources are allocated more efficiently in MVC investments. As an example, PVC funds tend to prefer late-stage investments (Leleux & Surlemont 2003). However, their superior non-financial resources (de Carvalho et al. 2008) are most needed in early-stage companies (Lin et al. 2019). GVC funds can crowd-in PVC funds in more early-stage companies (in a MVC investment) by reducing the risks of investment, and in that way, the non-financial resources are allocated more efficiently. In addition, PVC fund managers can spend less time fundraising and more time on non-financial support (Andrieu & Groh 2012, Colombo et al. 2016). Furthermore, it has been suggested that MVC can benefit themselves with a "second opinion" in decision-making processes (Brander et al. 2002, Gompers & Lerner 2004, Casamatta & Haritchabalet 2007), arguably increasing the quality of decisions.

The theory that is most often discussed in connection with MVC investments is the crowding-in effect. In MVC investments, PVC and GVC share the risks and improve their separate risk diversification. It has been suggested that MVC investments signal high quality and high potential, which could attract more funding in later financing rounds (Cumming & Johan 2013). In 2011, Svensson (2011) encouraged the Swedish government to design their venture capital as fund-of-funds to increase the crowding-in effect of Swedish GVC. Only five years after this proposal, the Swedish government created Saminvest, a new GVC fund, to make new investments only indirectly through PVC funds (Saminvest 2020).

To sum up, previous research shows that MVC investments result in the highest level of both innovation and performance. The suggested explanation for these results is that MVC can allocate non-financial resources more efficiently than other VC types. GVC should be structured to crowd in PVC and subsidise the high risks associated with early-stage investments. Based on previous research, we expect that MVC will generate the highest level of innovation and formulate the following two hypotheses:

H4: Mixed venture capital is more effective than either private venture capital or governmental venture capital in supporting innovation

3 Data and Methods

This study follows a quasi-experimental design using an observational data sample of VC investments from 2004 to 2014, structured as panel data. Besides, we use two kinds of variables: *VC type* as the independent variables and *innovation* as the dependent variables. VC types are categorized into three categories: PVC, GVC, MVC. Four innovation indicators are involved: patent grants, patent citations, trademark rights, and industrial design rights. Further, the empirical framework includes fixed-effects regression models to test the innovative impact of each VC type and difference-in-differences models to draw inferences on causality.

3.1 Data

3.1.1 VC data

We obtain data on Swedish VC investments from the Swedish Private Equity & Venture Capital Association (SVCA)[4]. The dataset contains 2 617 investments in Swedish entrepreneurial companies from 1968 to 2020. The dataset includes information on VC-backed companies, their associated investors, and the year of the first round of investments.

We collected additional information on the VC-backed companies and the control group (see section 3.2.2 Construction of the control group) using Retriever Business[5]. We supplement each VC-backed company and its counterpart in the control group with registration year, ROA, number of employees, and economic sector. Additional information on VC investors is also collected so that each investment can be categorized as either PVC, GVC, or MVC. The Swedish GVC-funds are: Industrifonden, Almi Invest AB, Innovationsbron AB, Fouriertransform AB, and Inlandsinnovation AB (Tillväxtanalys 2020)[6]. We also add Swedish government-owned universities to the list of GVC-funds (even though they are not "funds", strictly speaking). All other investors are categorized as PVC funds. Suppose one or more GVC-funds and PVC-funds invest in the same portfolio company directly. In that case, it is categorized as a MVC investment[7]. We were not able to access data on foreign GVC-investments. However, foreign GVC is assumed to be negligible since many GVC entities aim to support local or regional innovation (Leleux & Surlemont 2003).

Figure 2 shows the original number of VC investments in Swedish entrepreneurial companies from 1996 to 2020. Figure 2 displays a low frequency of VC investments until the 2000s and a dramatic climb after that, reaching its peak in 2018. According to

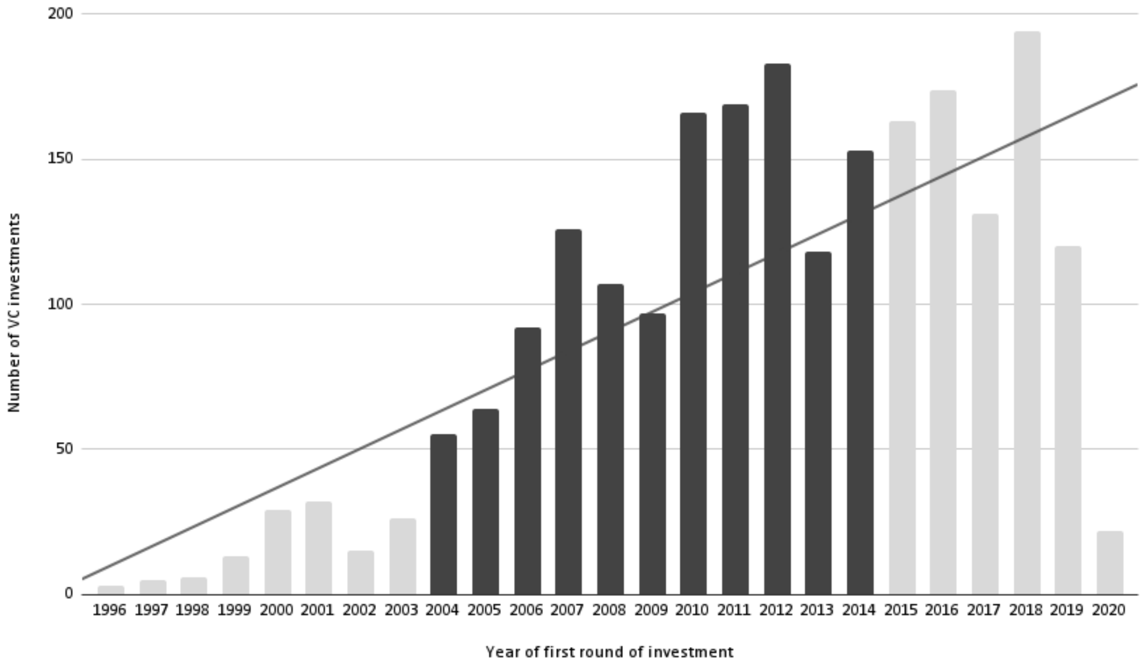
[4] SVCA is an independent, non-profit association for companies and individuals operating in the Swedish private equity area. The association's objective is to promote a well-functioning private equity market in Sweden and spread knowledge about the Swedish private equity market among the general public.

[5] The Retriever Business database contains basic and financial information of all firms registered in Sweden (Löfsten 2016).

[6] Tillväxtanalys is tasked by the Swedish government to highlight the areas that are most important for welfare growth.

[7] In an earlier draft, we also included indirect investments in the definition of MVC. However, we excluded them in the final thesis because the general partners commonly manage the funds' investments without any impact from the limited partners. The previous definition yielded similar results.

FIGURE 2. Total number of VC investments in Swedish entrepreneurial companies



Notes: Data was not systematically collected until around 2012 and has not yet been compiled in full for the year 2020. The darker bars indicate the observations included in our sample.

SVCA, the low frequency at the beginning of the dataset results from data not being collected systematically until around 2012. Figure 2 indicates a more extensive adjustment of the frequency in 2004. As far as we know, there were no significant changes in the VC market at that time, so we assume that the number of investments from 2004 and moving forward constitutes a reasonably representative sample of VC investments made in Sweden during that period. Therefore we exclude the VC investment data before 2004.

TABLE 2: SUMMARY OF INVESTOR DATA (2004-2014)

	No. of investments	No. investors	Minimum	Maximum	Mean	Median
VC investment duration			0	16	5.4	6
No. of VC investors per VC-backed firm			1	9	1.2	1
PVC	724	180	1	35	4.7	2
GVC	394	14	1	314	36.5	9
MVC	163					

Notes: No. of investments depicts the total number of investments for each VC type. "VC investment duration" is the duration, in years, from the first round of VC investment until exit (an IPO or acquisition).

Table 2 suggests that the average duration of VC investment (from the first round of investment to exit) is 5.4 years. To be consistent with these descriptive data and previous studies (e.g. Bertoni & Tykvová 2012, Dahlberg & Sörling 2019), we choose a 5-year observing period. Since we need five years of innovation data and our innovation data extends to 2018, our sample of VC investments has to end with 2014. For example, for a company that receives VC in 2014, patent grants will be observed in the years spanning from 2014 to 2018. So far, we have ruled out the VC investments from 1996 to 2003 and 2015 to 2020. Before these adjustments, the sample includes 2 617 VC investments in Swedish entrepreneurial companies. After the adjustments, our sample includes 1 336 VC investments in Swedish entrepreneurial companies during 2004-2014. Since the first round of financing is the earliest VC entrance and the beginning point for VC investors to exercise their influence, we only keep the first round of VC investment for our observations. We do not consider additional rounds of financing. Therefore, 33 additional observations are excluded from the original dataset. The complete process of data filtering can be seen in Appendix A.1.

Table 2 also summarises the number of investments and investors per VC type during the sampled period (2004-2014). As we can see, PVC funds made the highest amount of VC investments during this period while also showing the lowest amount of investments per fund. PVC is also the type of VC with the highest number of unique investors (more than 11 times the sum of both GVC and MVC). MVC has no investor data since MVC only refers to joint investments between PVC and GVC. Thus there are no MVC investors. It is noteworthy that each GVC fund manages an average of 36 firms and a maximum of 314 firms (not including the approximately 200 continued commitments for the "maximum-fund" before 2004). In line with what previous studies have found (e.g. (Sahlman 1990, de Carvalho et al. 2008)), table 2 indicates that GVC fund managers usually have less time to spend on each portfolio company.

3.1.2 Innovation data

When examining the effect that VC has on innovation, previous studies have used different proxies for innovation. The most frequently used proxies are R&D, patent applications, or patent grants. The disadvantage of using R&D spending as a proxy for innovation is that it only captures resources allocated to produce innovation without accounting for companies effectiveness of converting R&D spending (input) into innovation (output) (Acs et al. 2002). Therefore, patent data is commonly considered a superior proxy for innovation (Kortum & Lerner 2000). Patent data is also a fairly reliable proxy for innovation and has been widely used in other studies (Burhan et al. 2017).

Patent data is generally preferred when having an innovation output orientation. But a specific kind of patent indicator need to be selected since patents can be measured at several stages – application, grant, or citation. Patent applications are sometimes preferred since it is closer in time to the actual invention. However, it is criticized for its uncertainty of being granted and its incapability to represent patents economic value. Patent grants give companies the legal right to "prevent others from making, using, or selling their invention without their permission" (EPO, Glossary)[8]. In this sense, a granted patent gives the owner exclusive rights to exploit monopoly profits, which indicates that the invention has economic value. Patent citations have proven to be a good indicator of the quality of patents (Trajtenberg 1990, Hall et al. 2005, Bernstein 2015, Griliches 1998, Alcácer & Gittelman 2006). It refers to the number of forwarding citations to a particular invention and is a good indication of the novelty and importance of the patent (Bernstein 2015). A quantified study by Duguet & MacGarvie (2005) has revealed that patent citations are associated with new knowledge, technology, and inventions. Based on the above comparison, we decide to use patent grants as a quantitative measure of innovation and patent citation as a qualitative measure.

The disadvantage of patent data is that not all innovations are patented (Bertoni & Tykvova 2015). To capture additional dimensions of innovation, we include trademark rights and industrial design rights as additional output-oriented measures of innovation. Andersson et al. (2019) utilizes both patents and trademarks as a complementary measure to design rights and explains how they can capture different dimensions of innovation. Precisely, patents can capture innovations in terms of function and efficiency. Trademarks can protect brands of particular goods or services from others as a marketing asset (Zhou et al. 2016). It is also a sample that the firm starts market activities to do commercialization (Douglas & Shepherd 2002). Designs or industrial design rights (IDR) can capture aesthetic dimensions of innovations such as appearance, shape, and style(Andersson et al. 2019).

It is worth noting that there is no perfect measure of innovation. All measures only serve as partial innovation indicators because innovation itself is a very inclusive and broad term (Rogers 1998). By including several proxies for innovation (patent grants, patent citations, trademarks, and design rights) as separate dependent variables, this study captures a more comprehensive picture of the total innovation output from Swedish entrepreneurial companies receiving VC-backing.

We collect patent data from the European Patent Office's PATSTAT Global - 2020 Au-

[8]This is the definition of a patent, from the European Patent Office Glossary https://www.epo.org/service-support/glossary.html

tumn edition, which includes more than 100 million patent documents across industries and relevant legal event data from around 40 authorities worldwide (EPO 2021). It is a platform for users who want to collect patent applications, grants, publications, and citation information. Then, we gather trademarks and design data from both the Swedish Patent and Registration Office (PRV's) database and EUIPO's trademark and design database. To match the innovation data with specific VC-backed firms, we use the PAtLink database (which is run by the Swedish House of Finance). It provides matching information between unique organization numbers and patent and trademark ID numbers. The patent data consists of all patent application numbers filled by Swedish firms from 1990 to 2018. The trademarks data has matching information between unique organization numbers and trademark ID numbers that end with 2017.

3.1.3 Variables

Since both patent grants and design rights have limited lifespans, it makes sense to depreciate them over time. We use a 15% depreciation rate for patent grants, passive citations, and design rights, as 15% is the most frequently used depreciation rate in previous studies on innovation[9]. However, trademarks are not depreciated since they can be renewed every ten years and can be protected for an unlimited amount of time. We define the qualitative measure of granted patents weighted by citation numbers as "passive citations" and, thereby, passive citations inherit the depreciation rate of patent grants.

We code our dependent variables as stock variables (cumulative stacking) to include the effects of the depreciation rates and stock up the innovative impact of VC investors up to five years after the first round of VC funding. We use stock variables in both our DiD and FE regressions. However, we also present some descriptive statistics using flow variables to provide a more comprehensive overview of our dependent variables (see table 5). Note that the applications of stock variables are used in similar studies on innovation (e.g. Andersson et al. 2019, Bertoni & Tykvova 2015).

In our regressions, we also use the logarithmic transformation of all our dependent variables to reduce variation and alleviate problems with potential outliers (Lütkepohl & Xu 2012, Chemmanur et al. 2010). As implied by table 4, our dataset contains some extreme outliers. Using logarithmic values of innovation proxies is the standard approach to deal with outliers in previous studies (e.g. Chemmanur et al. 2014, Bertoni & Tykvova 2015, Acs et al. 2002, Kortum & Lerner 2000). However, logarithmic transformation is mainly for regression purposes; we do not regard it as a part of the definition of each dependent variable. The ways of defining each dependent variable in time t are listed in Equations

[9]The robustness checks in Bertoni & Tykvova (2015) suggest that the depreciation rate makes very little difference when examining the effect of different VC types on innovation.

1, 2, 3 and 4.

$$P_t^{stock} = P_t^{flow} + P_{t-1}^{stock} * (1 - 0.15) \tag{1}$$

$$PC_t^{stock} = 0.5 * P^{flow} + 0.5 * C^{flow} + P_{t-1}^{stock} * (1 - 0.15) \tag{2}$$

$$TM_t^{stock} = TM_t^{flow} + TM_{t-1}^{stock} \tag{3}$$

$$IDR_t^{stock} = IDR_t^{flow} + IDR_{t-1}^{stock} * (1 - 0.15) \tag{4}$$

We also include several control variables in the regressions. Since our sample is distributed across industries and over time, we create an industry and a year dummy variable to control[10] for these effects. Besides, because companies' age might correlate with their number of patent grants, passive citations, trademarks, and design rights, we also control for age. Thus, the control variables involved in the models are industry, year, and age.

3.2 Empirical Framework

3.2.1 Fixed Effects and Difference-in-Differences

We use a fixed effect (FE) regression model to test our hypothesis in a multivariate setting. We adopt the panel data with fixed effects models to eliminate omitted variable bias since only using cross-sectional data for an OLS regression could result in inconsistency and systematic bias. When estimating the effects of VC on innovation, results could be biased by unobserved, firm-level characteristics that determine both whether a company receives VC or not and their level of innovation (Bertoni & Tykvova 2015). An example of unobserved heterogeneity is the differences between firms in different industries, i.e. firms that operate in the same industry share more similar characteristics to one another than firms operating in different industries. We also include a random effects (RE) model as a robustness check. A limitation of FE and RE regressions is that they can only identify correlation but not causality because there might be multicollinearity between dependent and omitted variables (Stock and Watson, 2019).

Since Hirukawa & Ueda (2011) noted that there might be a reverse-causality issue, we use a difference-in-differences (DiD) model to draw inferences about causality and control for reverse-causality simultaneously. The underlying logic of the causality is that something that happened at one point in time is likely to affect something that happens in the future

[10]Strictly speaking, it is impossible to control for variables in a FE model, but we adjust for them. To avoid confusion, we will still call them control variables.

and not the other way around. The DiD model estimates the average treatment effect by comparing the effects of a treatment group with a control group before and after an event (Abadie 2005). The model requires a control group to eliminate any general trends that are not due to the effect of the treatment. The critical assumption of DiD is that the outcome in the treatment and control group would follow the same trend over time in the absence of the treatment (Clair & Cook 2015). Figure 3 shows how DiD is used to capture the average treatment effect.

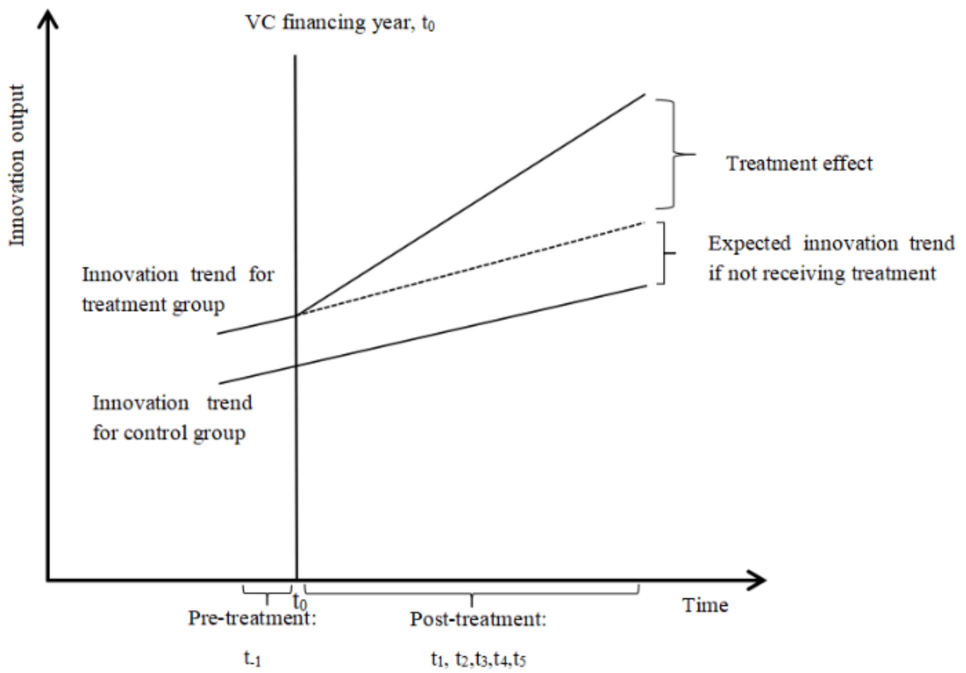


FIGURE 3. Difference-in-Difference method and treatment effect

3.2.2 Construction of the control group

The control group was constructed using nearest neighbour matching, without replacement – also called greedy matching (Austin 2011). We used a sample population of all registered Swedish companies from 2003 to 2013. We collected the data from the Retriever Business database, using a ratio of 1:1 and an acceptable deviation rate of ± 50% on each variable. The matching process resulted in 440 twin pairs (a total of 880 firms). The detailed matching process is displayed in Appendix A.1

We include several matching criteria to ensure similarity. First, one notable selection bias is that VC funds tend to invest in companies that already appear highly innovative (Hirukawa & Ueda 2011, Hoenig & Henkel 2015). Therefore, we select previous patent applications as our first matching criteria. We use patent applications rather than patent grants, as they better reflect similarities between firms' resources and innovation strategies. As our second criteria, we use economic sectors since VC funds tend to invest in specific industries where their network and competence are exceptionally high (Sorenson & Stuart 2001). Third, we select the year before VC investment to account for any time-related variables that might affect the likelihood of firms receiving VC, e.g. fluctuations in the general economy or the VC market. Fourth, we include profitability as a measure of risk-aversion. In theory, PVC fund managers will select their investments based on their level of risk-aversion (mentioned in the theory section, also used as a criterion by Boucly et al. 2011). Fifth and last, firm size has proven to be a significant determinant for VC managers in the process of investment selection (see, e.g. Engel & Keilbach 2007, Boucly et al. 2011). So we select the employee numbers to reflect firm size.

To show that the treatment and control group are similar, we compare the mean, median, minimum and maximum values in table 3. In addition, we add two-sample t-tests with unequal variance in appendix A.3 to show statistically that the two groups are similar.

TABLE 3: TREATMENT GROUP VS CONTROL GROUP

	Treatment group					**Control group**				
	Mean	Std.Dev.	Median	Min	Max	Mean	Std.Dev.	Median	Min	Max
No. of employees	103	947	8	1	19,143	105	1,032	8	1	21,001
ROA (%)	-17	44	-5	-276	152	-16	41	-6	-182	90
Previous patents	3	24	0	0	465	3	19	0	0	384

Notes: This table displays the descriptive statistics of the treatment and control group criteria.

3.2.3 Empirical models

For the FE regression, the baseline equation to be fitted is Equation 5 (model 1 and 2). In the equation, each VC type is coded as a dummy variable. The equation is also modified to adjust for potential year effects, using year dummies in model 3. For all models, we include age as a control variable[11] and cluster the standard errors on a firm-level (denoted as α for entity fixed effects) to mitigate problems of serial correlation[12].

$$Log(y_{it}) = \beta_1 PVC_{it} + \beta_2 GVC_{it} + \beta_3 MVC_{it} + \lambda AGE + \alpha_i + u_{it} \tag{5}$$

As an extra robustness check, we include a random effects (RE) model, where we adjust for both years and economic sectors using dummy variables. Economic sectors refer to

[11] We also ran these models including age^2, but decided to drop that variable because its effects were negligible (all coefficients and standard errors were less than 0.0004).

[12] We also ran similar models with White's standard errors adjusted for heteroscedasticity, but we excluded these models because the results were practically identical to those clustered on firm-level.

industries in an aggregate sense. The FE models already capture the differences between economic sectors (Bertoni & Tykvova 2015) and make us unable to provide different FE models with and without economic sector dummies. To chisel out the effect of economic sectors, a RE model is a good compromise between estimating effects for all economic sectors separately and pooling completely (Gelman & Hill 2006). Therefore, we use equation 6 to test both time and economic sector effects separately in model 4.

$$Log(y_{it}) = \beta_1 PVC_{it} + \beta_2 GVC_{it} + \beta_3 MVC_{it} + \lambda YEAR + \lambda AGE + \theta ES + \alpha_i + u_{it} \quad (6)$$

The DiD model is used to examine the difference between the pre-period and post-period of VC investment, in the difference between the treatment and control group. We include three dummies in the DiD models. The first dummy variable, for whether firms are in the treatment group (coded 1) or in the control group (coded 0), is defined as "VC". The second dummy variable shows whether observations are in the pre-VC investment period (coded 0) or in the post-VC investment period (coded 1). We define this variable as "Post". The third dummy variable represents the interaction between the two previous variables (coded 1 if the observation is both in the post-period and in the treatment group; otherwise, 0). The coefficient of the interaction variable is interpreted as venture capital's expected impact on innovation, also called the "DiD estimator". The OLS estimation used includes these dummy variables and the control variable age in the baseline equation 7.

$$Log(Y) = \alpha + \beta_1 POST + \beta_2 VC + \beta_3 (VC \times POST) + \lambda AGE + \epsilon \quad (7)$$

Further, equation 7 is modified into three additional models to test VC-effect in different situations. Model 6 adds year dummies to control for year effects. Model 7 adds economic sector (ES) dummies to control for economic sector effects. Model 8 (equation 8) uses both year and economic sector simultaneously to control for both year and economic sector effects. To test the effects of VC on all dependent variables, we run the above four models separately for each innovation proxy - patent grants, patent-weighted citations, trademarks, and design rights.

$$Log(Y) = \alpha + \beta_1 POST + \beta_2 VC + \beta_3 (VC \times POST) + \lambda AGE + \lambda YEAR + \delta ES + \epsilon \quad (8)$$

To sum up, we employ 4 FE models to test which type of VC is more effective to promote innovation and use 4 DiD models to test whether VC has a positive causality on innovations. We use these models to test all four hypotheses.

3.3 Sample description

After including control firms, our sample contains 880 firms over 16 years, covering the period spanning from 2003 to 2018, and equals 14 080 company-year observations. Our panel data is unbalanced; 1 980 observations are missing because there is no data available for firms before they are established. Also, since we could only access data on trademarks until 2017 and design data until 2016, all trademark observations in 2018 (880) and all design observations in 2017 and 2018 (1 760) are missing. The final sample size of patent grants is 12 100, passive citations 12 100, trademarks 11 220 and design rights 10 340.

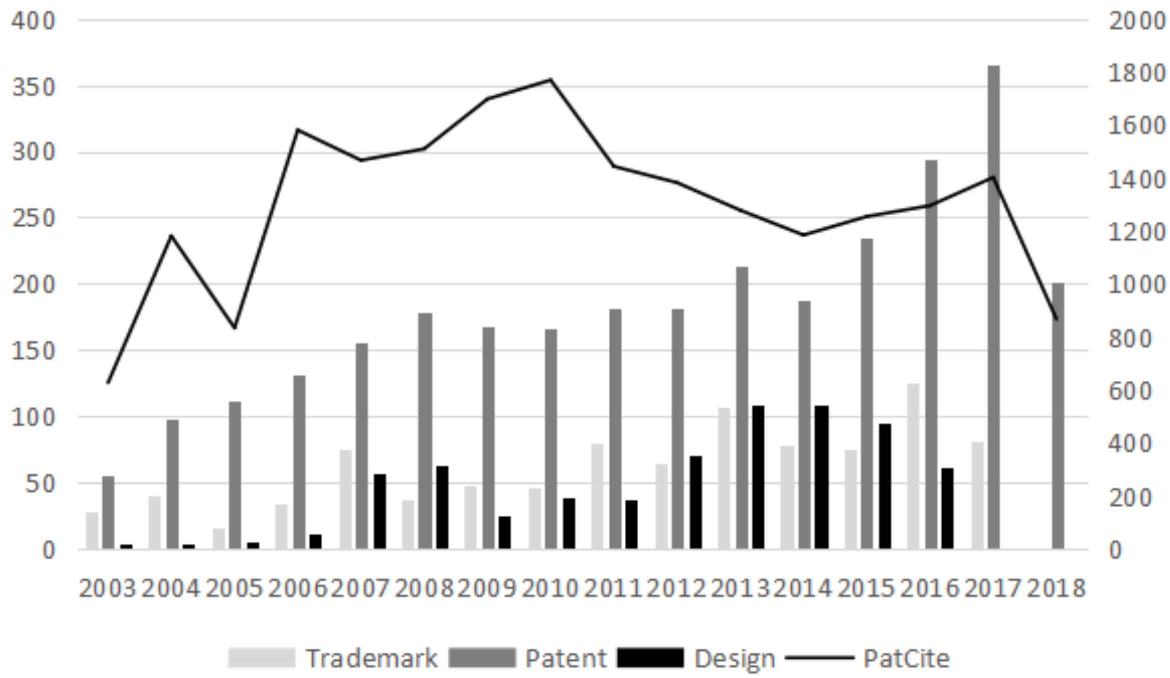


FIGURE 4. Yearly Distribution of Flow Innovations

Notes: The left y-axis marks the trademark, patent and design frequency, while the right y-axis measures the frequency of patent weighted by citations.

Figure 4 shows the frequency of different innovation proxies over the time 2003-2018. As we can see, all innovation proxies are displaying an upward trend, and the frequency of patent grants is higher than the sum of trademarks and design rights in most years. Also, patent citations have the highest frequency, showing more patent citations than patent grants. This is explained by the fact that patent citations include citations of all companies' published materials, including patent applications. Design rights have the lowest frequency during the years. This could indicate that, compared with other measures of innovation, VC investors may promote less innovation in product appearance, shape and materials measured by designs.

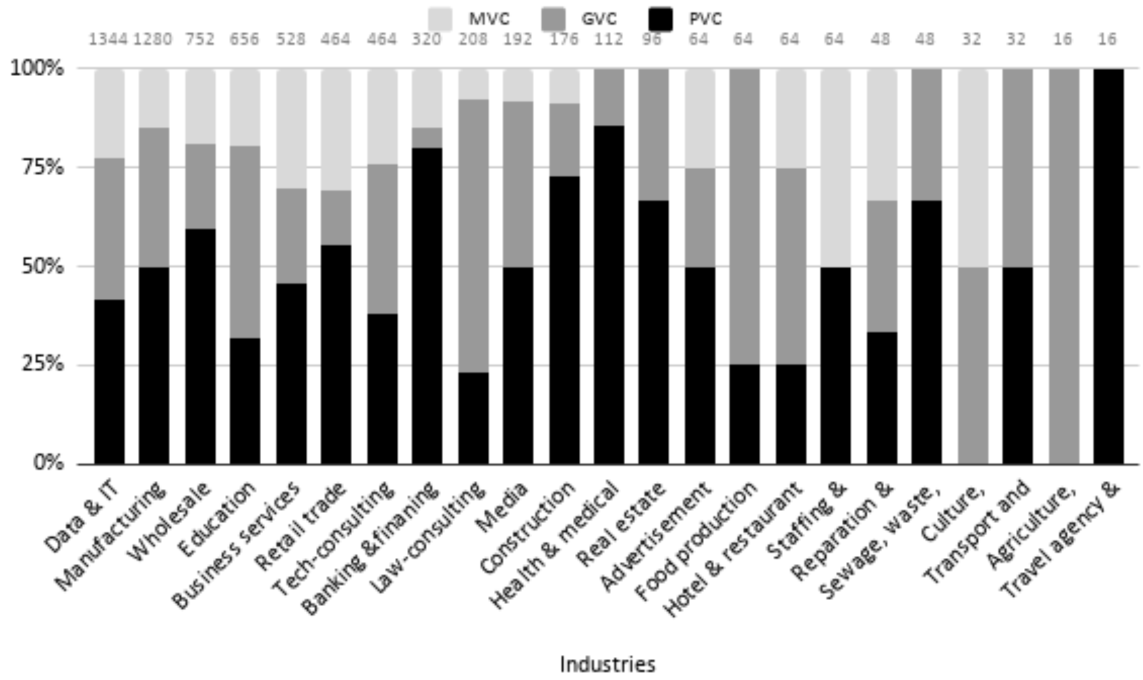


FIGURE 5. Economic sector distribution of sample firms

Figure 5 shows the sample distribution by economic sector. Since our control group mimics the sectors of the treatment group, we only display the treatment group in this figure. The two most popular economic sectors are "Data, IT and telecommunication", with 1 344 observations (84 VC investments over 16 years) and "Manufacturing and industry" with 1 280 observations (80 VC investments). The two least popular sectors are "Agriculture" and "Travel agencies", each with only 16 observations (1 VC investment). From figure 5, we can also see that PVC and GVC avoid investing in the same companies. In relative numbers, PVC is over-represented in the "health&medical" and "travel agency" sectors. In absolute numbers, PVC favours "Manufacturing" while refraining from investing in "Agriculture" and "Culture". In contrast and as theory dictates, GVC support these "less attractive" industries such as "Agriculture" and "Food production". However, GVC is absent in the Travel agency sectors, where PVC dominates.

TABLE 4: STOCK INNOVATION VARIABLES

	Obs	Mean	Std. Dev.	Min	p99	Max	Skewness	Kurtosis
Patents	12100	1.48	10.34	0	26	314	17	363
PatCite	12100	2.95	24.43	0	62	1052	22	701
Trademarks	11220	0.55	2.21	0	10	44	9	121
Designs	10340	0.23	4.17	0	3	201	35	1425

Notes: Dependent variables are all cumulative. Patent and design data is deprecated by 15%, and trademarks are not depreciated.

The descriptive statistics of the dependent variables are presented in Table 4. The mean of innovation variable implies how many stock patents, trademarks and designs that one sample company possessed on an average level. For example, the mean value of the patent is 1.48, indicating that, on average, one firm has 1.48 units of depreciated patent stock. The table shows that patent stock is higher than both the trademark and design stock. Besides the mean, p99 refers to the value at the 99 percentile. By comparing p99 and Max, we can determine the presence of extreme values or outliers. Furthermore, the level of kurtosis can also indicate outliers. In Table 4, we see that the kurtosis levels are high, even extreme, indicating that there are extreme outliers in the dataset. The data is highly skewed to the right, explained by the most common observation being "0". To mitigate problems with outliers, we use logarithmic transformation on all our dependent variables. After logarithmic transformation: log(patents) has a skewness of 3.0 and kurtosis of 12.0, log(trademarks) has a skewness of 2.5 and kurtosis of 8.3, log(designs) has a skewness of 13.9 and kurtosis of 203. The log(passive citations) has a skewness of 3.3 and a kurtosis of 13.6. The skewness and kurtosis after logarithmic are primarily reduced and better suited for regression. The skewness and kurtosis after logarithm can still be considered on the high side. In the end, we decided to keep the outliers because most of the identified outliers came from PVC-backed companies and deleting them would wrongly increase the power of GVC and MVC-backed companies in the regression. To ensure the results are as accurate as possible, we instead mitigate skewness and kurtosis using the logarithm. Even though outliers affect the coefficients' power to some extent, it does not affect the significance.

TABLE 5: NUMBER OF INNOVATIONS BY VC AND NON-VC GROUPS

	Obs	**Mean**	**Std.Dev**	**Min**	**Max**	**Obs**	**Mean**	**Std.Dev**	**Min**	**Max**
Patent grants	VC-backed					Non-VC-backed				
PVC	3,076	0.369	2.286	0	51	3,076	0.303	1.998	0	40
GVC	1,789	0.121	0.498	0	6	1,789	0.066	0.403	0	7
MVC	1,185	0.316	1.465	0	26	1,185	0.125	0.604	0	8
Passive citations	VC-backed					Non-VC-backed				
PVC	3,076	3.504	36.136	0	1022	3,076	1.309	8.425	0	125.5
GVC	1,789	0.641	3.709	0	66	1,789	0.242	1.916	0	36
MVC	1,185	3.129	19.558	0	322	1,185	0.564	3.474	0	52
Trademarks	VC-backed					Non-VC-backed				
PVC	2,864	0.144	0.743	0	13	2,864	0.066	0.487	0	13
GVC	1,647	0.064	0.318	0	3	1,647	0.022	0.186	0	3
MVC	1,099	0.135	0.637	0	13	1,099	0.045	0.329	0	6
Design rights	VC-backed					Non-VC-backed				
PVC	2,652	0.052	0.754	0	27	2,652	0.195	2.747	0	77
GVC	1,505	0.019	0.395	0	14	1,505	0.002	0.077	0	3
MVC	1,013	0.006	0.189	0	6	1,013	0	0	0	0

Notes: The data in this table are presented as flow variables.

The table 5 summarises the innovation proxies for each VC type and their corresponding control groups. Here we present flow variables instead of stock variables to show the average number of new, for example, patent grants per year, subdivided into VC-type and corresponding control groups. Table 5 provides a first indication of what outcome we can expect from our empirical models. Apart from PVC-backed companies in the design rights proxy, all treatment firms have larger means and standard deviation than their controls. Meaning that, on average, VC-backed companies generate more innovation (except designs) than their controls every year. However, they also have a more significant standard deviation. Furthermore, it appears that PVC often has the highest level of dispersion. The number of observations is, in descending order, from PVC-backed companies, GVC-backed companies and MVC-backed companies. Nevertheless, the number of observations for each VC-backed category is large enough for the intended models.

4 Results

4.1 Multivariate results

We test our hypothesis in a multivariate setting to show the effects of different VC types on innovation. We run four different regression models, all adjusted for VC-backed companies age. All models have their standard errors clustered on firm-level to adjust for serial correlation. To control for time-invariant heterogeneity, we use fixed effects (FE) in models 1, 2, and 3 (which also capture economic sector-specific effects). In model 4, we also present a random effects model to demonstrate our results' robustness. Though, it is worth noting that the Hausman test indicates that a random effects model will be inconsistent (see Appendix A.4). Tables 6, 7, and 8 show the results of VC type on each innovation proxy.

4.1.1 VC's effect on patents

Table 6 displays the effects of VC type on patent grants and passive citations. Model 1 tests both H2 and H3 and shows the differences between PVC-backed, GVC-backed, and non-VC-backed companies. The results in model 1 indicate that there is no difference in patent grants between PVC-backed, GVC-backed, and non-VC-backed companies. However, passive citations indicate that receiving GVC results in higher patent quality. Regarding H2 that PVC is more effective than GVC in supporting innovation, the results from the patent data indicate the opposite – that GVC is more effective because it leads to higher patent quality. These results also reject H3 since there is a difference between GVC-backed and non-VC-backed companies.

In model 2, we include MVC investments. The evidence shows that receiving MVC results in more patent grants and higher patent quality. In model 3, we add a year dummy to the model. We see that the results from model 2 are robust even after adjusting for years. Model 2 and 3 test hypothesis H4, that MVC is more effective in spurring innovation than either PVC or GVC. The results support this hypothesis - MVC is the most effective type of VC to spur patent grants and patent quality. Receiving MVC will result in approximately 17%[13] more patent grants and 26% more passive citations.

[13] According to Benoit (2011) about the estimation of $e^{\beta} \approx \beta - 1$, we apply the equation $\hat{\beta} \approx e^{\beta} - 1$ to calculate the average percentage beta effect. In this way, 1 unit increase in X corresponds to approximately $e^{\beta} - 1$ percentage effect on Y.

TABLE 6: EFFECTS OF VC TYPE ON PATENT GRANTS AND PASSIVE CITATIONS

	Patent grants				Passive citations			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
PVC	0.046	0.037	0.038	0.045 **	0.053	0.044	0.040	0.050 **
	(0.038)	(0.038)	(0.039)	(0.014)	(0.042)	(0.042)	(0.042)	(0.018)
GVC	0.059	0.051	0.053	0.053 **	0.097 *	0.089 *	0.090 *	0.090 ***
	(0.039)	(0.039)	(0.039)	(0.017)	(0.043)	(0.043)	(0.043)	(0.021)
MVC		0.155 *	0.157 *	0.160 ***		0.229 **	0.228 **	0.233 ***
		(0.072)	(0.072)	(0.021)		(0.085)	(0.085)	(0.027)
Age	0.029 ***	0.030 ***	0.031 ***	0.006 ***	0.025 ***	0.027 ***	0.028 ***	0.006 ***
	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)
N	9 730	12 100	12 100	12 100	9 730	12 100	12 100	12 100
Model specification								
Dependent variable	Patent grants	Patent grants	Patent grants	Patent grants	Passive citations	Passive citations	Passive citations	Passive citations
Regression type	FE	FE	FE	RE	FE	FE	FE	RE
Year dummy	No	No	Yes	Yes	No	No	Yes	Yes
Sector dummy	No	No	No	Yes	No	No	No	Yes

Notes: Each company-year is one observation. Patent grants and passive citations are logarithmic, cumulative, and depreciated by 15%. In model 1, MVC and its counterparts in the control group are excluded. Therefore, the number of observations in model 1 is different from the number of observations in the other models. FE/RE indicates the use of fixed or random effects. The mean is significantly different from zero at the 5% (*), 1% (**), or 0.1% (***) level of significance. Values within parentheses are the standard error for each coefficient. All standard errors are clustered on firm-level to ensure entity fixed effects.

4.1.2 VC's effect on trademark rights

TABLE 7: EFFECTS OF VC TYPE ON TRADEMARK RIGHTS

	Model 1	Model 2	Model 3	Model 4
PVC	0.140 ***	0.133 ***	0.138 ***	0.146 ***
	(0.031)	(0.031)	(0.031)	(0.011)
GVC	0.081 *	0.075 *	0.075 *	0.077 ***
	(0.031)	(0.031)	(0.031)	(0.014)
MVC		0.244 ***	0.246 ***	0.249 ***
		(0.063)	(0.063)	(0.017)
Age	0.020 ***	0.021 ***	0.023 ***	0.002
	(0.002)	(0.002)	(0.002)	(0.001)
N	9 022	11 220	11 220	11 220
Model specification				
Dependent variable	Trademarks	Trademarks	Trademarks	Trademarks
Regression type	FE	FE	FE	RE
Year dummy	No	No	Yes	Yes
Sector dummy	No	No	No	Yes

Notes: Each company-year is an observation. Trademark rights are logarithmic, cumulative numbers. The number of observations is different from table 6 since we could only access data until 2017 for trademarks (and not 2018 as in the patent data). FE/RE indicates the use of fixed or random effects. The mean is significantly different from zero at the 5% (*), 1% (**), or 0.1% (***) level of significance. Values within parentheses are the standard error for each coefficient. All standard errors are clustered on firm-level to ensure entity effect fixed.

Table 7 displays the effects of VC type on trademark rights. The results of model 1 show that PVC and GVC result in more trademarks and that PVC is the most effective in supporting innovation. These results are in line with H2 but different from what is indicated in Table 6, meaning that whether H2 is true or false is dependent on what innovation proxy is used. H3 is again rejected since GVC is significantly different from non-VC-backed companies. Model 2 and 3 show that all types of VC will result in more trademarks. MVC will result in approximately 28% more trademarks, PVC in 14% more trademarks, and GVC in 8% more trademarks. These results support H4, that MVC is the most effective type of VC to spur innovation.

4.1.3 VC's effect on design rights

TABLE 8: EFFECTS OF VC TYPE ON DESIGN RIGHTS

	Model 1	Model 2	Model 3	Model 4
PVC	0.024	0.025	0.023	0.022 **
	(0.021)	(0.021)	(0.021)	(0.008)
GVC	0.014	0.014	0.017	0.018
	(0.022)	(0.022)	(0.022)	(0.009)
MVC		-0.019	-0.018	-0.018
		(0.014)	(0.014)	(0.012)
Age	0.005 **	0.005 **	0.005 **	0.002 ***
	(0.002)	(0.002)	(0.002)	(0.000)
N	8 314	10 340	10 340	10 340
Model specification				
Dependent variable	Designs	Designs	Designs	Designs
Regression type	FE	FE	FE	RE
Year dummy	No	No	Yes	Yes
Sector dummy	No	No	No	Yes

Notes: Each company-year is an observation. Design rights are logarithmic, cumulative, and depreciated by 15%. The number of observations is different from the other tables because we could only access design data until 2016. FE/RE indicates the use of fixed or random effects. The mean is significantly different from zero at the 5% (*), 1% (**), or 0.1% (***) level of significance. Values within parentheses are the standard error for each coefficient. All standard errors are clustered on firm-level to ensure entity effect fixed.

Table 8 displays the effects of VC type on design rights. This table shows no differences in design rights between any VC-backed and non-VC-backed group of companies. Thus, receiving VC has no (quantitative) effect on design rights. Therefore, neither H2 nor H4 holds when innovation is proxied by design rights. However, these results are in line with H3.

Model 4 in Tables 6, 7, and 8 is a random effect (RE) regression model adjusted for both a year and an economic sector dummy. We present this model as an extra robustness check. Model 4 results in minor changes to the coefficients and generally increase the significance levels. However, a Hausman test indicates that the random effects model is inconsistent (see Appendix A.4). Thus, the results from our FE regression models (Models 1-3) are more reliable.

To sum up, the evidence related to H2 is fragmented – patent quality is higher in GVC-backed companies, but the effect on trademarks is more substantial in PVC-backed companies. PVC and GVC have an insignificant effect on patent grants. Design rights were unaffected by all types of VC. The opposite of H3 is found; GVC-backed companies can lead to higher-quality patents and significantly more trademarks. Thus GVC spurs more innovation than non-VC-backed companies. In line with H4, the results show that MVC is the most effective VC type in spurring innovation.

4.2 Causality

There is some evidence of reverse causality and that innovation attracts VC rather than the other way around (Hirukawa & Ueda 2011). Therefore, we use four DiD models (models 5-8) to conclude the causality of VC and innovation. The main focus is on the interaction variable "Post×VC" in each model.

4.2.1 The causality of VC and patents

Table 9 shows that the number of granted patents increases by an average of 11%[14] after receiving VC financing, compared with its peers (the average treatment effect). The patent quality (proxied by passive citations) increases by an average of 14%. However, one should be careful in interpreting the percentage of "patent quality", as it does not describe but only gives an indication of the economic value of the patents. Both results are statistically significant at the 0.1% significance level, showing that receiving VC results in more patent grants and higher quality patents. In addition, the coefficient of "Post" indicates that the number of patent grants increases by approximately 8% after VC financing, after controlling for year and industry effects (model 8). Note that this coefficient includes both the treatment and the control group. The VC variable shows no difference between the treatment and control groups without considering the time of VC investment. Again, focusing on the interaction variable, Post×VC, the effects of receiving VC are both positive and strongly significant for both patent grants and passive citations. These results support H1, that VC has a positive impact on innovation.

For both patent grants and passive citations, model 8 has the highest explanatory power of the four models. The adjusted R^2 for all models is less than 0.2, meaning that our models explain less than 20% of the variance in both dependent variables. However, this is expected and acceptable because this study aims not to construct the optimal regression model for innovation but to test how VC affects innovation.

[14] Computed by taking the exponent of the coefficient, subtract one and multiply by a hundred. For example, (exp(0.101)-1)×100 = 11%

TABLE 9: DIFFERENCE-IN-DIFFERENCE OF PATENT GRANTS AND PASSIVE CITATIONS

	Patent grants				**Passive citations**			
	Model 5	Model 6	Model 7	Model 8	Model 5	Model 6	Model 7	Model 8
Post×VC	0.101 ***	0.101 ***	0.103 ***	0.103 ***	0.131 ***	0.131 ***	0.134 ***	0.134 ***
	(0.025)	(0.025)	(0.023)	(0.023)	(0.030)	(0.030)	(0.028)	(0.028)
Post	0.167 ***	0.125 ***	0.164 ***	0.077 ***	0.151 ***	0.142 ***	0.147 ***	0.083 **
	(0.018)	(0.023)	(0.017)	(0.022)	(0.022)	(0.028)	(0.020)	(0.026)
VC	0.007	0.007	0.000	0.000	0.020	0.020	0.011	0.011
	(0.018)	(0.018)	(0.017)	(0.017)	(0.022)	(0.022)	(0.021)	(0.021)
Age	0.008 ***	0.008 ***	0.006 ***	0.006 ***	0.008 ***	0.008 ***	0.005 ***	0.005 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.000	-0.073 *	-0.149 *	-0.264 ***	0.042 *	-0.026	-0.152	-0.267 **
	(0.014)	(0.035)	(0.064)	(0.071)	(0.017)	(0.043)	(0.078)	(0.087)
Adjusted R^2	0.068	0.069	0.175	0.176	0.048	0.048	0.154	0.155
N	12 100	12 100	12 100	12 100	12 100	12 100	12 100	12 100
Model specification								
Dependent variable	Patent grants	Patent grants	Patent grants	Patent grants	Passive citations	Passive citations	Passive citations	Passive citations
Year effect	No	Yes	No	Yes	No	Yes	No	Yes
Industry effect	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Patent grants and passive citations are logarithmic, cumulative and depreciated by 15%. The mean is significantly different from zero at the 5% (*), 1% (**), or 0.1% (***) level of significance. Values within parentheses are the standard error for each coefficient.

4.2.2 The causality of VC and trademark rights

TABLE 10: DIFFERENCE-IN-DIFFERENCE OF TRADEMARK RIGHTS

	Model 5	Model 6	Model 7	Model 8
Post×VC	0.201 ***	0.201 ***	0.203 ***	0.203 ***
	(0.019)	(0.019)	(0.018)	(0.018)
Post	0.066 ***	-0.023	0.070 ***	-0.032
	(0.013)	(0.017)	(0.013)	(0.017)
VC	0.054 ***	0.054 ***	0.051 ***	0.051 ***
	(0.013)	(0.013)	(0.013)	(0.013)
Age	0.003 ***	0.003 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.044 ***	-0.036	0.063	-0.045
	(0.010)	(0.025)	(0.051)	(0.056)
Adjusted R^2	0.072	0.078	0.099	0.106
N	11 220	11 220	11 220	11 220
Model specification				
Dependent variable	Trademarks	Trademarks	Trademarks	Trademarks
Year effect	No	Yes	No	Yes
Industry effect	No	No	Yes	Yes

Notes: Trademark rights are logarithmic and cumulative. The mean is significantly different from zero at the 5% (*), 1% (**), or 0.1% (***) level of significance. Values within parentheses are the standard error for each coefficient. Standard errors of 0.000 means that the standard error is less than 0.0005, not that it is absolute zero.

Table 10 displays the results of trademark rights. As shown by coefficients of Post×VC, in models 5 to 8, VC-backed companies' trademark rights registrations are expected to increase by 22% after receiving VC financing than non-VC-backed companies. This effect is highly significant at the 0.1% level, in support of H1. Again, the explanatory power (indicated by adjusted R^2) is potent in model 8.

4.2.3 The causality of VC and design rights

TABLE 11: DIFFERENCE-IN-DIFFERENCE OF DESIGN RIGHTS

	Model 5	Model 6	Model 7	Model 8
Post×VC	-0.006	-0.006	-0.006	-0.006
	(0.011)	(0.011)	(0.011)	(0.011)
Post	0.023 **	0.017	0.023 **	0.012
	(0.008)	(0.009)	(0.008)	(0.010)
VC	0.018 *	0.018 *	0.017 *	0.017 *
	(0.007)	(0.007)	(0.007)	(0.007)
Age	0.003 ***	0.003 ***	0.002 ***	0.002 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.027 ***	-0.044 **	-0.038	-0.062
	(0.006)	(0.014)	(0.030)	(0.033)
Adjusted R^2	0.030	0.030	0.037	0.040
N	10 340	10 340	10 340	10 340
Model specification				
Dependent variable	Designs	Designs	Designs	Designs
Year effect	No	Yes	No	Yes
Industry effect	No	No	Yes	Yes

Notes: Trademark rights are logarithmic and cumulative. The mean is significantly different from zero at the 5% (*), 1% (**), or 0.1% (***) level of significance. Values within parentheses are the standard error for each coefficient. Standard errors of 0.000 means that the standard error is less than 0.0005, not that it is absolute zero.

Table 11 shows that VC does not affect the number of registered design rights (because the interaction variable, Post×VC, is insignificant in all models). In addition to the evidence from the multivariate analysis, this means that VC does not affect innovation when proxied by design rights.

4.2.4 The treatment effect of VC

To better show how receiving VC affects innovation, we present Figure 6. This figure compares the mean value between the treatment and the control group, for each innovation proxy, from one year before VC investment to 5 years after VC investment. T0 is the year of VC financing. There is no year of VC financing for the control group. Therefore, each control firm "inherits" the year of VC financing from its corresponding twin in the treatment group. Thus, T0 for the control group should be interpreted as the year that a "control firm" was most likely to receive VC.

Figure 6 shows that before VC investment, the control group has the same trend in patent grants as the treatment group. However, after receiving VC financing, the number of patent grants for VC-backed companies increase more. Regarding passive citations, VC-backed companies always keep a higher level than non-VC-backed companies, which means that the patent quality is higher for VC-backed companies. In the third graph, the steeper slope of the treatment group indicates that, on average, VC-backed companies have more trademark registration than non-VC-backed companies, and this difference is increasing the first years after VC investment. The tendency is for the control group to have more design rights registrations. However, the results are insignificant likely because of the low number of design rights in total for the sample (an average of 0.02 design rights per firm).

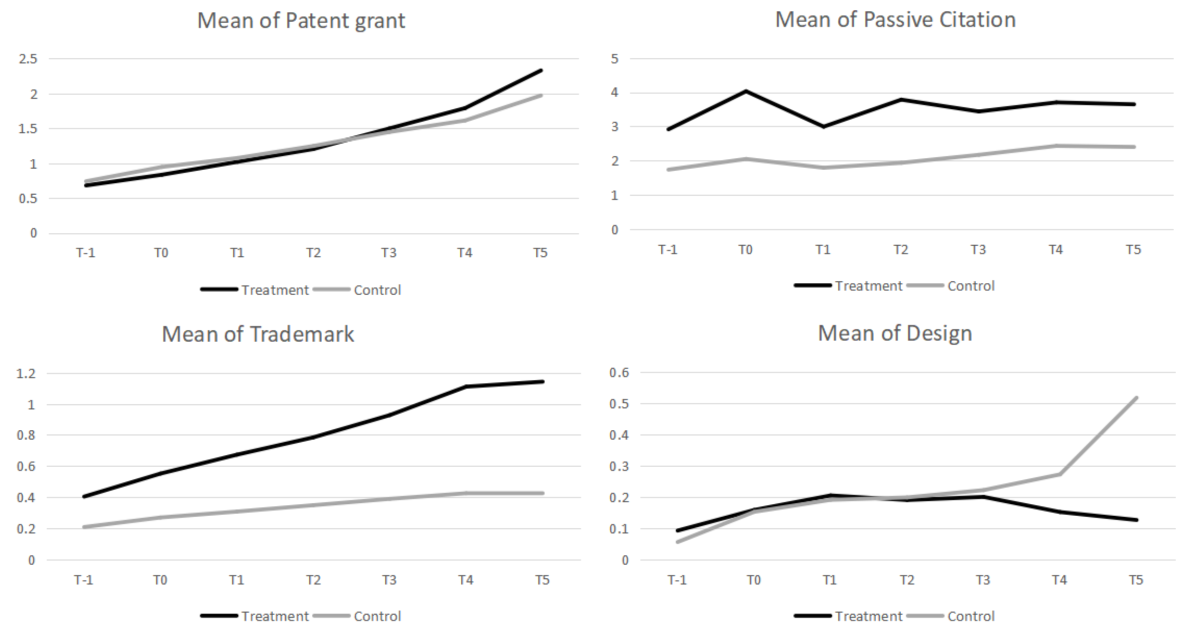


FIGURE 6. Innovation trend over observing years

To sum up the causality results, VC has a highly significant and positive impact on patent grants, passive citations, and trademarks. The results for design rights are insignificant. In total, this supports hypothesis 1 (that VC has a positive impact on innovation), also after controlling for reverse-causality.

5 Discussion

Hypothesis 1 is that *VC has a positive effect on innovation.* Supporting H1, the results from both the FE models and DiD models show that VC has a positive and highly significant effect on innovation. The results of patent grants are in line with the large body of studies conducted outside of Sweden – in the US (Kortum & Lerner 2000), Germany (Tykvova 2000), Spain (Arque-Castells 2012) and Europe (Engel 2002, Bertoni & Tykvova 2015)[15].

The results show that VC can remove financial constraints and provide entrepreneurial companies with valuable non-financial-support. Previous work has shown that both financial (Caliendo & Kopeinig 2008, Gompers & Lerner 2004, Jeng & Wells 2000) and non-financial support is important components when looking at the effects that VC has on innovation (de Carvalho et al. 2008, Lin et al. 2019). Note that the results are independent of the VC managers' ability to identify and select innovative portfolio companies, as this was adjusted for in the construction of the control group. We add new knowledge to the previous literature by showing that the results are robust also for patent quality and trademarks. There can be several reasons why the results for design rights are insignificant. We suggest that the trust in, or the expected value of, a design right does not have as high a reputation as trademarks and patents. Therefore, entrepreneurial companies might initially choose to focus on innovation rights with a higher reputation. An indication of the lower trust, or the relatively lower value of design rights, is the low number of design rights in relation to trademarks and patents in our sample (see Table 4). Apart from design rights, the collected evidence shows that VC has a highly significant and positive effect on innovation in Sweden, also after controlling for reverse-causality.

Hypothesis 2 is that *PVC is more effective than GVC in supporting innovation.* Hypothesis 3 is that *there is no difference in the degree of innovation between GVC-backed companies and non-VC-backed companies.* The FE regression model 1 answers hypotheses 2 and 3. Since H2 and H3 are tested by the same model, we discuss them together. The results are not as straightforward as for H1 but show a more complex picture than we initially expected. The results show that for entrepreneurial companies, receiving PVC increases the number of registered trademarks more than receiving GVC, but receiving GVC results in higher patent quality. Receiving PVC results in 14% more trademarks. Receiving GVC results in 8% more trademarks and 9% more patent citations. Thus, hypothesis 2 is inconclusive, and hypothesis three is rejected.

We suggest four explanations for these results. First, we argue that GVC funds' objective to spur innovation makes them focus more on patent quality. Instead, PVC funds focus more on commercializing products and services (reflected in the higher number of registered trademarks). This argument is supported by the findings of Hellmann & Puri (2000), that PVC is better at commercializing and bringing innovative products to market through trademark registration.

[15] Though Sweden is a part of Europe, Swedish data was not included in these European studies.

Second, PVC funds may advise their portfolio companies to keep the high-quality innovation secret due to spillover effects. In contrast, GVC funds should promote patenting of high-quality innovations to spur more innovation and increase spillover effects. This argument would explain GVC-backed companies' higher-quality patents. Under this assumption, taxpayers' money is used efficiently to increase short-term innovation and long-term welfare.

Third, the results can be explained by differences in risk preference, making GVC and PVC target companies at different stages. As an indicator of early- or late-stage investments, we use Figure 7, which shows the average age of the portfolio companies at the first round of investment, by VC-type. As indicated by the figure, GVC funds invest in more early-stage companies while PVC invests in more late-stage companies. These differences align with the theory of underinvestment in early-stage companies and can explain the different outcomes of different innovation proxies. Earlier-stage companies are likely to emphasize higher-quality patents because they are at a stage where all focus is on completing products and services to start generating revenue. Late-stage companies are more likely to have passed this stage and are instead focusing on commercialization.

Fourth, GVC makes continuous follow-up investments even for non-growing companies, while PVC usually only makes follow-up investments if portfolio companies grow (Engberg et al. 2021). In this sense, GVC supports innovation more persistently and puts less pressure on companies returns and growth rates, allowing GVC funds portfolio companies to focus more on innovation.

It is a little unexpected that we do not see any effects of PVC or GVC on the number of granted patents in Sweden. These results contrast the findings of Bertoni & Tykvova (2015), who found that PVC is significantly positive on both patent grants and patent quality and that there is no difference between GVC and non-VC-backed firms. However, Bertoni & Tykvova (2015) only examine the two most high-tech industries and do not include any observations from Sweden. That suggests that something might be different in Sweden from other European countries. As a first difference, in Sweden, PVC and GVC have limited differences in contractual choice, rendering PVC funds private contractual clauses less significant (Isaksson et al. 2004), suggesting that the level of risk aversion in Sweden is not as different between general partners in PVC funds and GVC funds as in other countries. Besides, assuming that increased employment leads to increased innovation, Engberg et al. (2021) indicate no apparent connection between VC funding and increased employment in Sweden, at least not as for a short period as five years.

Hypothesis 4 is that *mixed venture capital is more effective than either private or governmental venture capital in supporting innovation*. We use models 2, 3, and 4 to answer H4. The results of the models support H4 on both patent grants, passive citations, and trademarks. These results are explained by the fact that diverse groups with complementary strengths support MVC-backed companies (Colombo et al. 2016). In addition, MVC investments have access to a larger pool of capital than either PVC funds or GVC funds alone (Brander et al. 2015). Also, it is known that MVC is the type of VC that has the largest share of employees with advanced education in Sweden (Engberg et al. 2021), potentially resulting in more innovation. Appropriately enough, since the restructuring of the Swedish GVC in 2016, GVC investments are more often structured as indirect investments, in the form of fund-of-funds, which – as shown by both our study and Bertoni & Tykvova (2015) – are likely to result in synergies that lead to increased innovation.

6 Conclusions

In the contemporary, governments have been increasing their engagements to spur innovation through VC markets. But previous research has shown that GVC does not impact innovation. With the above contradiction, this study examines GVC's effectiveness in spurring innovation in one of the most innovative countries globally, Sweden. Applying a combined FE and DiD, we test how different types of VC investors affect innovation in their respective portfolio companies.

Based on the results and discussion, we conclude that VC, in general, has a significant and positive effect on innovation, even after controlling for reverse causality. From the perspective of innovation indicators, the results are especially strong for trademarks, but patent grants and passive citations are also positive and highly significant. However, the number of industrial design rights is unaffected by companies receiving VC.

The results show that MVC is the most effective VC type in spurring innovation, while different advantages separately merit PVC and GVC. Regarding MVC, it has the most positive and highest significant effects on innovation among all VC types, increasing patent grants by 17%, passive citations by 26%, and trademarks by 28%. These results suggest that PVC and GVC, when investing together in the same companies, can increase innovative efficiency by focusing on each investor's complementary strengths.

As for GVC, entrepreneurial companies that receive GVC show significant increases in trademarks and passive citations (8% and 9% respectively), indicating that GVC effectively promotes commercialization and high-quality patents. However, there are no significant effects on number of patent grants or industrial design rights. In short, the evidence of GVC-backed companies shows that the taxpayers' money is used effectively to spur innovation in Swedish entrepreneurial companies.

As for PVC, entrepreneurial companies that receive PVC significantly increase their number of trademarks on average 14%, implying that PVC is more effective at commercializing companies' innovations and bringing them to market. There are no effects on patent grants, passive citations, or industrial design rights. However, we argue that PVC funds likely advise their portfolio companies to keep the high-quality innovation secret due to spillover effects.

This study has a theoretical implication for the literature of VC and innovation. It is a pioneering study to compare different VC types effect on innovation in a Swedish setting. In addition, this study has a practical implication for entrepreneurial companies who wish to get founded through VC funds. Entrepreneurial companies should focus on getting funding from the type of VC investor whose strengths best match the company's innovative strategy.

6.1 Limitations and further work

Admittedly, there are some limitations of our study. First, the results of PVC and GVC on patent grants might have turned significant in the multivariate setting had we used a larger sample of control firms, as the variance might have decreased. We used a ratio of 1:1, while Bertoni & Martí (2011) argue that a ratio of one treatment firm to ten control firms might be better. Therefore we suggest further research to test our result with a larger sample of control groups.

To examine the research question from another angle, one might consider using a population of all Swedish firms with (e.g.) patent grants and look at differences between the number of patent grants between VC-backed and non-VC-backed firms. Instead, we used the sample of all known VC-backed firms and compared them with a control group constructed from a population of all Swedish firms. We suggest further research select a sample from a different perspective to studying this topic as a robustness test.

In addition, since our study is an observational study using a non-random sample, selection bias cannot be eliminated, just reduced to reasonable levels during the construction of a control group. In practice, it is not possible to make every matched pair of firms identical in all aspects (ceteris paribus) and only differ in "treatment or no-treatment".

Therefore, what matching criteria are used is a balance. Including too many matching criteria would result in a smaller sample due to the stricter criteria. Including too few variables would result in more significant selection bias.

Moreover, we decided to add previous patent applications as a matching criterion to indicate the companies' level of innovation, based on the study of Engel & Keilbach (2007). Nevertheless, previous trademarks and design are not considered for matching. In this sense, we suggest that further research should consider all innovation indicators when matching a control group.

At last, we only consider whether companies receive VC-backing or not; we do not consider the VC amount or the number of financing rounds. As a consequence, we cannot correctly compare the effectiveness of different VC types in converting capital into innovation. Therefore, we suggest further research to include the amount of VC invested. Furthermore, we did not use any qualitative measures of trademarks and designs. Thus finding quality measures of trademarks and designs and comparing their inventiveness are suggested for further research.

References

Abadie, A. (2005), ‘Semiparametric Difference-in-Differences Estimators’, *The Review of Economic Studies* **72**(1), 1–19.

Acs, Z. J., Anselin, L. & Varga, A. (2002), ‘Patents and innovation counts as measures of regional production of new knowledge’, *Research Policy* **31**(7), 1069–1085.

Alcácer, J. & Gittelman, M. (2006), ‘Patent Citations as a Measure of Knowledge Flows: The Influence of Examiner Citations’, *The Review of Economics and Statistics* **88**(4), 774–779.

Andersson, D., Tell, F., Huila, A. & Ekman, A. (2019), Designing value: Design protection and the market value of firms, *in* ‘DRUID Conference’.

Andrieu, G. & Groh, A. P. (2012), ‘Entrepreneurs’ financing choice between independent and bank-affiliated venture capital firms’, *Journal of Corporate Finance* **18**(5), 1143–1167.

Armour, J. & Cumming, D. (2006), ‘The legislative road to silicon valley’, *Oxford Economic Papers* **58**(4), 596–635.

Arque-Castells, P. (2012), ‘How venture capitalists spur invention in Spain: Evidence from patent trajectories’, *Research Policy* **41**(5), 897–912.

Arrow, K. (1962), Economic welfare and the allocation of resources for invention, *in* ‘The Rate and Direction of Inventive Activity: Economic and Social Factors’, National Bureau of Economic Research, Inc, pp. 609–626.

Audretsch, D. & Thurik, R. (1999), Innovation, Industry Evolution, and Employment: Introduction, *in* D. B. Audretsch & A. R. Thurik, eds, ‘Innovation, industry evolution, and employment’, Cambridge; New York and Melbourne:, pp. 1–12.

Austin, P. C. (2011), ‘An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies’, *Multivariate Behavioral Research* **46**(3), 399–424.

Beck, T. & Demirguc-Kunt, A. (2006), ‘Small and medium-size enterprises: Access to finance as a growth constraint’, *Journal of Banking & finance* **30**(11), 2931–2943.

Benoit, K. (2011), ‘Linear regression models with logarithmic transformations’, *London School of Economics, London* **22**(1), 23–36.

Berger, A. N. (2014), Small business lending by banks, *in* P. M. Allen N. Berger & J. O. S. Wilson, eds, ‘The Oxford Handbook of Banking, Second Edition’, Oxford: Oxford University Press.

Bernstein, S. (2015), ‘Does Going Public Affect Innovation?’, *The Journal of Finance* **70**(4), 1365–1403.

Bertoni, F., Colombo, M. G. & Quas, A. (2015), ‘The patterns of venture capital investment in europe’, *Small business economics* **45**(3), 543–560.

Bertoni, F., D’Adda, D. & Grilli, L. (2019), ‘Self-selection of entrepreneurial firms in thin venture capital markets: Theory and empirical evidence’, *Strategic Entrepreneurship Journal* **13**(1), 47–74.

Bertoni, F. & Martí, J. (2011), ‘Financing Entrepreneurial Ventures in Europe: The Vico Dataset’, *SSRN Electronic Journal* .

Bertoni, F. & Tykvova, T. (2015), ‘Does Governmental Venture Capital Spur Invention and Innovation? Evidence from Young European Biotech Companies’, *Research Policy* **44**(4), 925–935.

Bertoni, F. & Tykvová, T. (2012), Which form of venture capital is most supportive of innovation?, Discussion Paper No. 12-018, ZEW Discussion Papers.

Bottazzi, L. & Da Rin, M. (2002), ‘Venture capital in Europe and the financing of innovative companies’, *Economic Policy* (34), 229–269.

Boucly, Q., Sraer, D. & Thesmar, D. (2011), ‘Growth LBOs’, *Journal of Financial Economics* **102**(2), 432–453.

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

Brander, J. A., Du, Q. & Hellmann, T. (2015), ‘The effects of government-sponsored venture capital: international evidence’, *Review of Finance* **19**(2), 571–618.

Burhan, M., Singh, A. K. & Jain, S. K. (2017), ‘Patents as proxy for measuring innovations: A case of changing patent filing behavior in Indian public funded research organizations’, *Technological Forecasting and Social Change* **123**, 181–190.

Caliendo, M. & Kopeinig, S. (2008), ‘Some Practical Guidance for the Implementation of Propensity Score Matching’, *Journal of Economic Surveys* **22**(1), 31–72.

Carpenter, R. E. & Petersen, B. C. (2002), ‘Is the Growth of Small Firms Constrained by Internal Finance?’, *Review of Economics & Statistics* **84**(2), 298–309.

Casamatta, C. & Haritchabalet, C. (2007), ‘Experience, screening and syndication in venture capital investments’, *Journal of Financial Intermediation* **16**(3), 368–398.

Chan, Y.-S. (1983), 'On the positive role of financial intermediation in allocation of venture capital in a market with imperfect information', *The Journal of Finance* **38**(5), 1543–1568.

Chemmanur, T. J., Loutskina, E. & Tian, X. (2014), 'Corporate venture capital, value creation, and innovation', *The Review of Financial Studies* **27**(8), 2434–2473.

Chemmanur, T., Loutskina, E. & Tian, X. (2010), 'Corporate venture capital, value creation, and innovation', *Boston College Working Paper* .

Clair, T. S. & Cook, T. D. (2015), 'Difference-in-differences methods in public finance', *National Tax Journal* **68**(2), 319–338.

Coad, A. & Rao, R. (2008), 'Innovation and firm growth in high-tech sectors: A quantile regression approach', *Research policy* **37**(4), 633–648.

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

Cumming, D. J., Grilli, L. & Murtinu, S. (2017), 'Governmental and independent venture capital investments in europe: A firm-level performance analysis', *Journal of corporate finance* **42**, 439–459.

Cumming, D. J. & Johan, S. A. (2013), *Venture Capital and Private Equity Contracting: An International Perspective*, Academic Press, Amsterdam.

Cumming, D. J. & MacIntosh, J. G. (2006), 'Crowding out private equity: Canadian evidence', *Journal of Business venturing* **21**(5), 569–609.

Cumming, D. & Johan, S. (2016), 'Venture's economic impact in Australia', *Journal of Technology Transfer* **41**(1), 25–59.

Dahlberg, E. & Sörling, S. (2019), The money of innovation: The impact of venture capital on innovation in sweden, Master's thesis, Department of Business Studies, Uppsala University.

Davis, T. J. & Stetson, C. P. (1985), 'Creating successful venture-backed companies', *Journal of Business Strategy* .

de Carvalho, A. G., Calomiris, C. W. & de Matos, J. A. (2008), 'Venture Capital as Human Resource Management', *Journal of Economics and Business* **60**(3), 223–255.

Deeds, D. L., Decarolis, D. & Coombs, J. E. (1997), 'The impact of firm-specific capabilities on the amount of capital raised in an initial public offering: Evidence from the biotechnology industry', *Journal of Business Venturing* **12**(1), 31–46.

Dorsey, T. (1979), Operating guidelines for effective venture capital funds management, Technical report, IC^2 Institute, The University of Texas at Austin.

Douglas, E. J. & Shepherd, D. (2002), 'Exploring investor readiness: assessments by entrepreneurs and investors in australia', *Venture Capital: An international journal of entrepreneurial finance* **4**(3), 219–236.

Duguet, E. & MacGarvie, M. (2005), 'How well do patent citations measure flows of technology? Evidence from French innovation surveys', *Economics of Innovation and New Technology* **14**(5), 375–393.

Dutta, S., Lanvin, B. & Wunsch-Vincent, S. (2017), *Global Innovation Index 2017*, Cornell University, INSEAD, and the World Intellectual Property Organization (WIPO).

Engberg, E., Tingvall, P. G. & Halvarsson, D. (2021), 'Direct and indirect effects of private-and government-sponsored venture capital', *Empirical Economics* **60**, 701–735.

Engel, D. (2002), The impact of venture capital on firm growth: an empirical investigation, Working Paper 02-02, ZEW Discussion Papers.

Engel, D. & Keilbach, M. (2007), 'Firm-level implications of early stage venture capital investment — An empirical investigation', *Journal of Empirical Finance* **14**(2), 150–167.

EPO (2021), 'Patstat', Website. European Patent Office (EPO).
URL: *https://www.epo.org/searching-for-patents/business/patstat.html*

European Court of Auditors (2019), Centrally managed eu interventions for venture capital: in need of more direction, Technical report, European Court of Auditors.

EVCA (2014), '2013 european private equity activity: statistics on fundraising, investments and divestments'.
URL: *http://www.evca.eu/media/142790/2013-European-Private-Equity- Activity.pdf*

Gelman, A. & Hill, J. (2006), *Data analysis using regression and multilevel/hierarchical models*, Cambridge university press.

Gompers, P. A. & Lerner, J. (2004), *The Venture Capital Cycle*, MIT Press.

Gompers, P., Kovner, A. & Lerner, J. (2009), 'Specialization and success: Evidence from venture capital', *Journal of Economics & Management Strategy* **18**(3), 817–844.

Gompers, P. & Lerner, J. (1999), 'An analysis of compensation in the us venture capital partnership', *Journal of Financial Economics* **51**(1), 3–44.

Gorman, M. & Sahlman, W. A. (1989), 'What do venture capitalists do?', *Journal of business venturing* **4**(4), 231–248.

Greene, P. G., Brush, C. G., Hart, M. M. & Saparito, P. (2001), 'Patterns of venture capital funding: is gender a factor?', *Venture Capital: An international journal of entrepreneurial finance* **3**(1), 63–83.

Griliches, Z. (1998), Patent statistics as economic indicators: a survey, *in* 'R&D and productivity: the econometric evidence', University of Chicago Press, pp. 287–343.

Hall, B. H. (2002), 'The financing of research and development', *Oxford review of economic policy* **18**(1), 35–51.

Hall, B. H., Jaffe, A. & Trajtenberg, M. (2005), 'Market Value and Patent Citations', *The RAND Journal of Economics* **36**(1), 16–38.

Hall, B. H. & Lerner, J. (2010), The financing of r&d and innovation, *in* 'Handbook of the Economics of Innovation', Vol. 1, Elsevier, pp. 609–639.

Hellmann, T. & Puri, M. (2000), 'The interaction between product market and financing strategy: The role of venture capital', *The review of financial studies* **13**(4), 959–984.

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

Hoenig, D. & Henkel, J. (2015), 'Quality signals? the role of patents, alliances, and team experience in venture capital financing', *Research Policy* **44**(5), 1049–1064.

Hood, N. (2000), 'Public venture capital and economic development: the scottish experience', *Venture Capital* **2**(4), 313–341.

Isaksson, A., Cornelius, B., Landström, H. & Junghagen, S. (2004), 'Institutional theory and contracting in venture capital: the swedish experience', *Venture capital* **6**(1), 47–71.

Jaffe, A. B. & Jaffe, A. B. (1996), *Economic analysis of research spillovers: Implications for the advanced technology program*, US Department of Commerce, National Institute of Standards and Technology.

Jeng, L. A. & Wells, P. C. (2000), 'The determinants of venture capital funding: evidence across countries', *Journal of corporate Finance* **6**(3), 241–289.

Jääskeläinen, M., Maula, M. & Murray, G. (2007), 'Profit distribution and compensation structures in publicly and privately funded hybrid venture capital funds', *Research Policy* **36**(7), 913–929.

Kerr, W. R. & Nanda, R. (2015), 'Financing innovation', *Annual Review of Financial Economics* **7**, 445–462.

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

Law, J., ed. (2018), *Risk Capital*, Oxford University, Oxford University Press.
URL: *https://www.oxfordreference.com/view/10.1093/acref/9780198789741.001.0001/acref-9780198789741-e-3301*

Leland, H. E. & Pyle, D. H. (1977), 'Informational asymmetries, financial structure, and financial intermediation', *The journal of Finance* **32**(2), 371–387.

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. (1999), 'The government as venture capitalist: The long-run impact of the SBIR program', *Journal of Business* **72**(3), 285–318.

Lerner, J. (2002), 'When bureaucrats meet entrepreneurs: The design of effective 'public venture capital' programmes', *Economic Journal* **112**(477), F73–F84.

Lerner, J. (2010), 'The future of public efforts to boost entrepreneurship and venture capital', *Small Business Economics* **35**(3), 255–264.

Lin, X., Xu, W., Zhang, B. & Yang, F. (2019), 'Does Venture Capital Spur Innovation or the Other Way Around? Evidence on the Significance of Investment Timing from China', *Growth and Change* **50**(1), 90–113.

Litvak, K. (2009), 'Venture capital limited partnership agreements: Understanding compensation arrangements', *University of Chicago Law Review* **76**(1), 161–218.

Luukkonen, T., Deschryvere, M. & Bertoni, F. (2013), 'The value added by government venture capital funds compared with independent venture capital funds', *Technovation* **33**(4-5), 154–162.

Löfsten, H. (2016), 'Business and innovation resources: Determinants for the survival of new technology-based firms', *Management Decision* **54**(1), 88–106.

Lütkepohl, H. & Xu, F. (2012), 'The role of the log transformation in forecasting economic variables', *15 CESifo Working Paper No. 2591. Empirical Economics* **42**, 619–638.

Parliamentary Audit Office (1996), Riksdagens revisorers förslag angående statligt engagemang i regionala investmentbolag, Technical report, Parliamentary Audit Office.

Popov, A. & Roosenboom, P. (2013), 'Venture capital and new business creation', *Journal of Banking & Finance* **37**(12), 4695–4710.

Repullo, R. & Suarez, J. (2000), 'Entrepreneurial moral hazard and bank monitoring: a model of the credit channel', *European Economic Review* **44**(10), 1931–1950.

Riksrevisionen (2014), Statens insatser för riskkapitalförsörjning – i senaste laget, Technical Report 1, Riksrevisionen.
URL: *https://www.riksdagen.se/sv/dokument-lagar/dokument/riksrevisionens-granskningsrapport/statens-insatser-for-riskkapitalforsorjning—$i_H 2B51$/html*

Rogers, M., ed. (1998), *The Definition and Measurement of Innovation*, University of Melbourne. Working paper 10/98.

Rosenbaum, P. (2002), Overt bias in observational studies, *in* 'Observational Studies', Springer Series in Statistics, Springer, New York, NY, pp. 71–104.

Sahlman, W. (1990), 'The Structure and Governance of Venture-Capital Organizations', *Journal of Financial Economics* **27**(2), 473–521.

Saminvest (2020), Saminvests årsredovisning 2020, Annual report, Saminvest.
URL: *https://www.saminvest.se/sites/default/files/documents/reports/2021-03/Saminvest-AR2020$_2$10323.pdf*

Sapienza, H. J. & Gupta, A. K. (1994), 'Impact of agency risks and task uncertainty on venture capitalist–ceo interaction', *Academy of Management journal* **37**(6), 1618–1632.

Schäfer, D. & Schilder, D. (2006), Informed capital in a hostile environment: the case of relational investors in germany, Technical report, Freiberger Arbeitspapiere.

Schultz, C. (2011), 'Financing stages of technology-based firms in germany', *International Journal of Entrepreneurship and Innovation Management* **14**(2-3), 206–221.

Sorenson, O. & Stuart, T. E. (2001), 'Syndication networks and the spatial distribution of venture capital investments', *American Journal of Sociology* **106**(6), 1546–1588.

Suzuki, K. (1996), 'Nihon ni okeru venture management no jittai (facts on venture managements in japan)', *Venture management no henkaku, edited by K. Yanagi and T. Yamamoto, Nihon Keizai Shimbumsha, Tokyo* .

Svensson, R. (2011), 'Statligt venture capital i stort behov av omstrukturering', *Ekonomisk Debatt* **39**(6), 14–27.

Tillväxtanalys (2017), Riskkapitalstatistik 2016 – venture capital, Technical report, Tillväxtanalys.
URL: *https://www.tillvaxtanalys.se/download/18.62dd45451715a00666f1dc64/1586366181907/statistik*$_{2}$017$_{0}$7$_{k}$*orrigerad*$_{2}$017$_{0}$9$_{2}$4*.pdf*

Tillväxtanalys (2020), Riskkapitalstatistik 2019 – venture capital, Technical report, Tillväxtanalys.
URL: *https://www.tillvaxtanalys.se/download/18.116e2ff51760b08af77f04e/1606921248196/Riskkapital*$_{2}$019*.pdf*

Trajtenberg, M. (1990), 'A Penny for Your Quotes: Patent Citations and the Value of Innovations', *The RAND Journal of Economics* **21**(1), 172–187.

Tykvova, T. (2000), 'Venture capital in germany and its impact on innovation', *Social Science Research Network Working Paper* pp. 1–30.

Tykvova, T. (2006), 'How do investment patterns of independent and captive private equity funds differ? evidence from germany', *Financial Markets and Portfolio Management* **20**(4), 399–418.

Tykvová, T. & Walz, U. (2007), 'How important is participation of different venture capitalists in german ipos?', *Global Finance Journal* **17**(3), 350–378.

Ueda, M. & Hirukawa, M. (2008), 'Venture Capital and Industrial 'Innovation'', *SSRN Electronic Journal* .

Vanacker, T., Collewaert, V. & Paeleman, I. (2013), 'The Relationship between Slack Resources and the Performance of Entrepreneurial Firms: The Role of Venture Capital and Angel Investors', *Journal of Management Studies* **50**(6), 1070–1096.

Wong, P. K., Ho, Y. P. & Autio, E. (2005), 'Entrepreneurship, Innovation and Economic Growth: Evidence from GEM data', *Small Business Economics* **24**(3), 335–350.

Zhou, H., Sandner, P. G., Martinelli, S. L. & Block, J. H. (2016), 'Patents, trademarks, and their complementarity in venture capital funding', *Technovation* **47**, 14–22.

A Appendix

A.1 The data filtering process of VC investments

TABLE 12: THE DATA FILTERING PROCESS

	No. of investments removed	No. of investments remaining	Notes
Part A: Data			
Initial dataset	-	2 271	The initial dataset from SVCA.
1996-2003	-131	2 141	The investment data in this period was not systematically collected.
2015-2020	-805	1 336	Since we target 5 years following investment and no matched innovation output data are available after 2018.
Repetitive date	-33	1 303	Repetitive data (several rounds of financing) are ruled out since we only target investments in the first financing round.
Part B: The matching process			
Negative or zero age	-305	998	Companies cannot receive VC before they are founded. Since we need to match the control firms at T(-1) we remove firms receiving investment at the age of 0.
No sector belongings	-209	789	These firms had no industry information in the Business retriever database, therefore we could not find their control twin using economic sector, instead they were excluded from the sample.
Missing values	-271	518	The value of important matching criteria-employee numbers and/or ROA are missing, leading to no matching basis.
No match	-78	440	Firms having no match because of their extremely high (or low) number of employee, patent applications or ROA.
Part C: The control group			
No. of VC-investments remaining		440	
Response rate		56% (440/789)	
No. of control firms		440	
Ratio treatment to control		1:1	

A.2 VC-backed companies age at VC investment subdivided by VC type

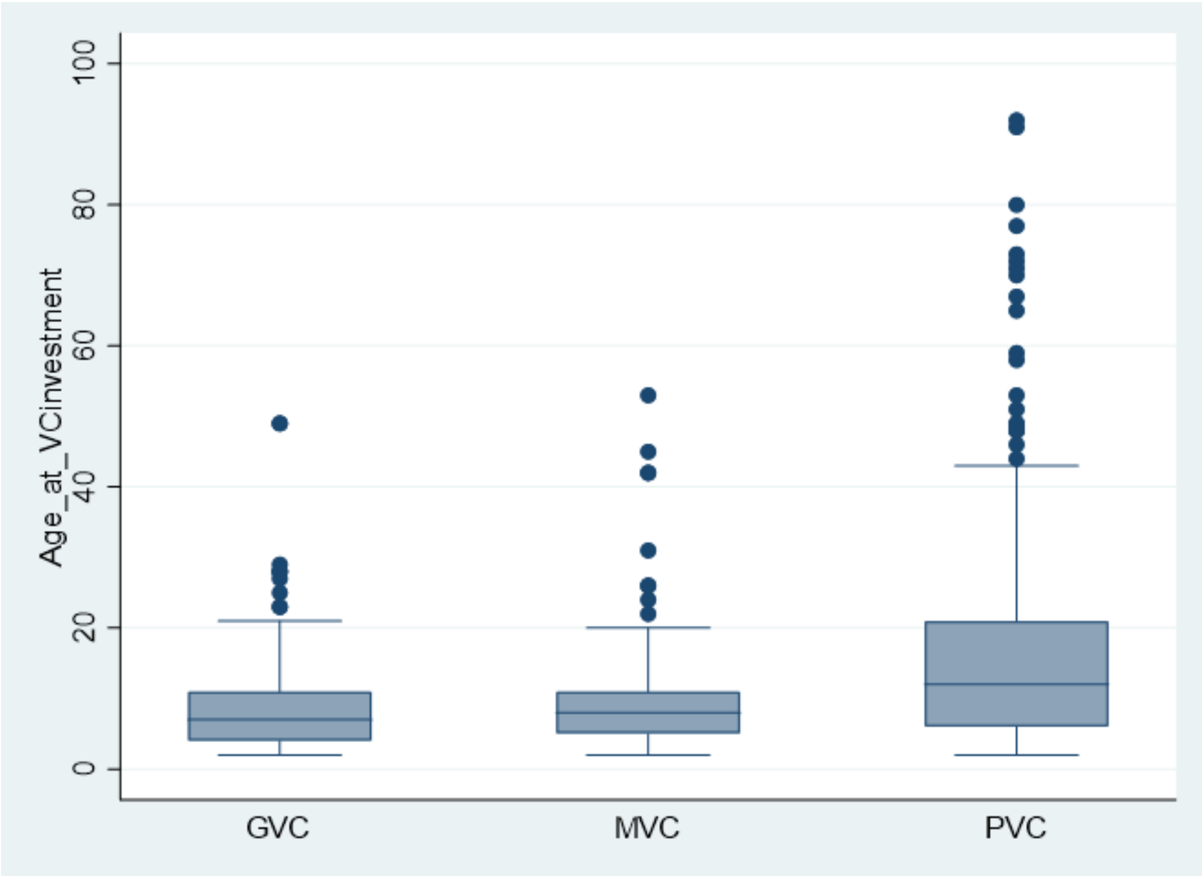


FIGURE 7. VC-backed companies age at VC investment subdivided by VC type

In addition to our tested hypotheses, it is customary to discuss potential crowding-in or crowding-out effects of governmental involvement (see e.g. Leleux & Surlemont (2003), Colombo et al. (2016), Parliamentary Audit Office (1996), Riksrevisionen (2014)). As theory states, PVC alone are insufficient to support all innovation. Figure 7 presents the VC-backed companies age at VC investment, as an indication of early- or late-stage investments we see that GVC invest more in early-stage companies and PVC invest more in late-stages companies. MVC lies between the average age of companies receiving either PVC or GVC, indicating that GVC has a crowding-in effect on PVC.

A.3 Detailed construction of the control group and Two-sample T-Test for treatment group and control group

When constructing a control group, it is essential to ensure that the control group is similar to the treatment group in the pre-treatment period. Any systematic differences between the treatment and control groups would otherwise bias the results, also known as selection bias. In this context, selection bias refers to the fact that companies receiving VC might have done so based on specific variables, e.g. having higher profitability than other firms or being more innovative than other firms. Notably, the selection bias can only be entirely avoided by a randomized experiment (Engel & Keilbach 2007). However, our sample is not randomly collected but conditional on Swedish firms having received VC-backing during 2004-2014. Thus it inherently includes some extent of selection bias. Though selection bias is impossible to eliminate, it can be mitigated to reasonable levels (Austin 2011). We use nearest neighbour matching, also known as greedy matching, to construct our control group and mitigate selection bias by setting up several matching criteria. Although we control for them and do matching in one year before the financing year, we can expect them to be similar the first years after the treatment event, since, e.g. patent applications usually takes 2 to 3 years to process (Arque-Castells 2012). We will get into the practical details of the construction of the control group in the next part.

A control group is needed for the DiD analysis. Companies included in the control group must be non-VC-backed and have the same likelihood of receiving VC as the firms that did. To constructing a control group, we employ the method of nearest neighbour matching, also known as greedy matching. Greedy matching is to select the nearest control firm (with the lowest distance) to match a given treatment firm, even if these control firms could better serve as a match for a subsequent treatment firm (Austin 2011, Rosenbaum 2002). We use a matching ratio of one control firms are matched to one treatment firm without replacement. Each control firm is the "twin" firm to its corresponding treatment firm. We paired them up in the year before the treatment firm received VC-backing since that point in time likely coincides with VC-investors screening processes. The sample of control firms is drawn from the population of all registered Swedish companies from the years 2003 to 2013 from the Retriever Business database (treated firms are excluded from the sampled population to ensure that the control group only contains non-VC-backed companies).

We include several matching criteria to ensure similarity. First, one notable selection bias is that VC funds tend to invest in companies that already appear highly innovative (Hirukawa & Ueda 2011, Hoenig & Henkel 2015). Therefore, we select previous patent applications as our first matching criteria. We use patent applications as our innovation proxy because it reflects similarities between firms' resources and innovation strategies. As our second criteria, we use economic sectors since VC funds tend to invest in specific industries where their network and competence is particularly high (Sorenson & Stuart 2001). Third, we select the year before VC investment to account for any time-related variables that might affect the likelihood of firms receiving VC, e.g. fluctuations in the general economy or the VC market. Fourth, we include profitability as a measure of risk-aversion, since at least in theory, PVC fund managers will select their investments based on their level of risk-aversion (mentioned in the theory section, also used as a criterion by Boucly et al. 2011). Fifth and last, firm size has proven to be a significant determinant for VC managers in the process of investment selection (see e.g. Engel & Keilbach 2007, Boucly et al. 2011). So we select the employee numbers to reflect firm size.

Notably, there is a trade-off between the level of similarity and the number of matches because firms with "no twin" are excluded from the analysis (Boucly et al. 2011). It can be tempting to add more matching criteria that have proven to be significant (e.g. geographical location (Sorenson & Stuart 2001)), but the more criteria we add, the less likely it is that we will find a match for each firm. Inspired by Boucly et al. (2011), we employ an acceptable deviation rate of $\pm$ 50% on each variable as a tolerant way to get a reasonably large sample and still eliminate a large portion of the selection bias. If several control firms are included in the $\pm$50% range, we use the "distance calculation" of equation 9 to identify and select the nearest control firm with "lowest distance".

$$Distance_{tc} = \frac{Emp_t - Emp_c}{Emp_t} + \frac{ROA_t - ROA_c}{ROA_t} + \frac{Pat_t - Pat_c}{Pat_t} \tag{9}$$

Notes: Where Distance_tc is the result of the difference in employee numbers (Emp), return on assets (ROA), and previous patenting (Pat) between the treatment firm (t) and the potential control firm match (c) at the year before VC investment.

The matching process resulted in 440 twin pairs (a total of 880 firms) – a "response rate" of 56%. Since we use five strict matching criteria and greedy matching, a modest response rate is expected and acceptable. The detailed matching process is also displayed in Appendix A.1 To check the similarity shared by the treatment group and the new control group, a comparison of the mean, median, minimum and maximum values are presented in table 3. Further, we add two-sample t-tests with unequal variance in Table ?? to show they are statistically similar.

TABLE 13: TWO-SAMPLE T-TESTS FOR TREATMENT VS CONTROL GROUPS

	Obs	Mean	Std. Err.	Std. Dev.	[95%Conf.	Interval]
Part A: Employee numbers						
	Obs	Mean	Std. Err.	Std. Dev.	[95%Conf.	Interval]
Control	440	105.139	49.202	1032.065	8.438	201.839
Treatment	440	103.280	45.155	947.175	14.533	192.026
Combined	880	104.209	33.372	989.967	38.711	169.707
diff.		1.859	66.782		-129.211	132.929
t-value		0.028				
Degrees of freedom		878				
p-value (two-tailed)		**0.978**				
Part B: Return on Asset(ROA)						
	Obs	Mean	Std. Err.	Std. Dev.	[95%Conf.	Interval]
Control	440	-16.520	1.936	40.619	-20.326	-12.714
Treatment	440	-17.056	2.077	43.558	-21.137	-12.975
Combined	880	-16.788	1.419	42.091	-19.573	-14.003
diff.		0.536	2.839		-5.037	6.109
t-value		0.189				
Degrees of freedom		878				
p-value (two-tailed)		**0.850**				
Part C: Previous Patent applications						
	Obs	Mean	Std. Err.	Std. Dev.	[95%Conf.	Interval]
Control	440	2.832	0.926	19.414	1.013	4.651
Treatment	440	3.457	1.142	23.959	1.212	5.702
Combined	880	3.144	0.735	21.795	1.702	4.586
diff.		-0.625	1.470		-3.510	2.260
t-value		0.425				
Degrees of freedom		878				
p-value (two-tailed)		**0.671**				

Notes: We used unequal variance when running the t-tests.

A.4 The Hausman test: Fixed or random effects?

TABLE 14: HAUSMAN TESTS FOR MODELS 1, 2, 3, 4

Patent grants				
	Coef. FE	Coef. RE	Difference	S.E.
PVC	0.037	0.087	-0.050	0.004
GVC	0.051	0.107	-0.056	0.004
MVC	0.155	0.210	-0.055	0.005
Age	0.030	0.023	0.007	0.001
Prob>chi2	**0.000**			
Passive citations				
	Coef. FE	Coef. RE	Difference	S.E.
PVC	0.044	0.090	-0.046	0.005
GVC	0.089	0.139	-0.050	0.006
MVC	0.229	0.279	-0.050	0.007
Age	0.027	0.020	0.006	0.001
Prob>chi2	**0.000**			
Trademarks				
	Coef. FE	Coef. RE	Difference	S.E.
PVC	0.133	0.188	-0.055	0.003
GVC	0.075	0.128	-0.054	0.004
MVC	0.244	0.301	-0.058	0.004
Age	0.021	0.013	0.008	0.000
Prob>chi2	**0.000**			
Design rights				
	Coef. FE	Coef. RE	Difference	S.E.
PVC	0.024	0.032	-0.007	0.003
GVC	0.014	0.024	-0.010	0.004
MVC	-0.019	-0.010	-0.009	0.004
Age	0.005	0.003	0.001	0.000
Prob>chi2	**0.000**			

Notes: If "Prob>chi2" is less than .05, it indicates that a random effects model will be inconsistent. In that case, we should use fixed effects models. Numbers displayed as 0.000 implies that the value is less than 0.0005 and not zero.