Governmental venture capital in Europe: screening and certification

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Abstract

This paper investigates the screening and certification abilities of government-managed venture capital (GVC) firms in Europe. Using a sample of European high-tech entrepreneurial companies, we show that GVC funding increases the likelihood that companies will receive private venture capital (PVC). Moreover, GVC-funded companies that have received a first round of PVC are at least as likely as other PVC-backed companies to receive a second round of PVC or to be listed or acquired. After ruling out alternative explanations, we interpret these results as positive evidence of GVC firms' abilities in selecting promising companies and certifying them to PVC investors.

Keywords: Venture capital, governmental venture capital, high-tech entrepreneurial ventures, screening, certification
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1 Introduction

Venture capital (VC) is an important source of financing for high-tech entrepreneurial companies (Gompers and Lerner 2001; Denis 2004). Moreover, VC investors complement their financial resources with a series of value-added activities – including financial, administrative, marketing, strategic and managerial support (Gorman and Sahlman 1989; Sahlman 1990) – that have an overall positive effect on the performance of companies in their portfolios (for a survey, see Da Rin et al. 2011). Although VC has been beneficial to the creation and development of many companies in the U.S. that have grown to employ thousands of people in a few years (e.g., Genentech, Google and Facebook), the VC market in Europe is less developed. Kelly (2011) notes that in Europe VC investments as a percentage of GDP are only one-fourth of the corresponding figure in the U.S. Typically, European high-tech entrepreneurial companies finance new investments with internal funds (Revest and Sapio 2012) and their growth is threatened by financial constraints (Carpenter and Petersen 2002a). This observation is troublesome because high-tech entrepreneurial companies are drivers of innovation, efficiency and growth of the countries where they operate (e.g., Audretsch 1995; Audretsch and Thurik 2001; Stam and Garnsey 2008).

The creation of an active VC market has therefore become a priority on the agenda of European policy makers (European Commission 1998; Da Rin et al. 2006). To achieve this goal, many European governments have established government-owned and managed VC (GVC) funds to complement the small supply of private VC (PVC). Examples of this type of government intervention include GIMV in Belgium, SITRA in Finland, BPI France in France, Piemontech in Italy, Scottish Enterprise in the UK, and Axis Participaciones Empresariales in Spain. Recent studies have shown that the effect of GVC on the performance (i.e., growth, innovation and efficiency) of their portfolio

companies is somewhat limited (e.g., Grilli and Murtinu 2014; Bertoni and Tykvovà 2015; Alperovych et al. 2015), which raises doubts regarding the effectiveness of this type of financing (e.g., Lerner 2009).

However, another potential source of added value that is associated with this initiative is that financing by GVC firms may facilitate access to PVC for their portfolio companies. Lerner (2002) argues that a rationale for GVC is the *certification hypothesis*. Specifically, if GVC firms can *screen* the market and identify promising entrepreneurial companies that are otherwise neglected by PVC firms, the receipt of GVC financing acts as a "stamp of approval" (Lerner 2002, p. F78). This endorsement *certifies* an entrepreneurial company's potential to outside investors (including PVC firms), thus facilitating the company's access to the PVC market.

Studies at the country and/or industry level have analyzed and found mixed evidence concerning whether the direct provision of public financing to the VC industry increases or crowds out the aggregate pool of PVC investments (e.g., Jeng and Wells 2000; Leleux and Surlemont 2003; del-Palacio et al. 2012). However, at the micro level, no studies have specifically investigated whether the alleged positive effect of GVC in stimulating PVC investment can be ascribed to a certification effect. To the best of our knowledge, Brander et al. (2015) conducted the only study that provides cross-country evidence regarding the relation between GVC financing and a portfolio company's additional fundraising. However, the study by Brander et al. (2015) is based on a sample that consists exclusively of VC-backed companies and lacks an adequate counterfactual of non-GVC-backed companies. In evaluating the certification role of GVC, we attempt to examine instead whether the companies that receive GVC would have attracted PVC had they not received GVC (Lach 2002). Overall, little is known concerning whether GVC firms can screen the market, select promising entrepreneurial companies and certify them to private investors.

In this paper, we attempt to reduce this gap by investigating whether obtaining GVC financing facilitates a high-tech entrepreneurial company's access to PVC financing because of a certification effect. Our hypotheses also address GVC's *screening ability*, i.e., GVC's capacity to select promising

entrepreneurial companies with the potential to create good investment opportunities for PVC. By offering a better understanding of these issues, this paper attempts to join the important policy debate regarding the effects of governmental efforts to stimulate the PVC industry in Europe (e.g., Da Rin et al. 2006; Lerner 2009; Cumming 2013).

The empirical analysis in this study uses a unique, company-level longitudinal sample of 8,277 European high-tech entrepreneurial companies that are extracted from the VICO dataset, which was created as a part of the VICO research project, promoted by the European Commission (see www.vicoproject.org). In our sample, 183 companies received their first round of financing from 81 different GVC firms that operate in seven European countries. Our hypotheses are tested with two alternative approaches; one approach performs a counterfactual analysis through a propensity score matching, and the other approach uses an endogenous switching regression model.

Our results show that receiving GVC funding makes an entrepreneurial company three times more likely to receive a first round of PVC. Second, the entrepreneurial companies that were selected by the GVC firms that have received a first round of PVC are at least as likely as other PVC-backed companies to receive a second round of PVC or to have a successful exit, i.e., they have the same probability to yield good investment opportunities for PVC. We interpret these results as positive evidence of GVC firms' abilities to screen the market, select promising companies and certify them to PVC investors. Our results are robust to different estimation methodologies and many possible alternative explanations.

This paper is structured as follows. In the next section, we review the literature on both the role of government intervention in the VC market and certification theory. We then develop three research hypotheses on GVC screening and certification. Section 3 describes the data and variables. Sections 4 and 5 present the two different approaches that we adopt to test our hypotheses and the results of each approach. In particular, Section 4 describes the matching algorithm that is used to select the sample of non-GVC-backed entrepreneurial companies and their associated results from an event-history model. Section 5 focuses on the switching regression model with endogenous switching.

Section 6 concludes the paper by discussing the policy implications, describing the limitations of the analysis and suggesting several avenues for future research.

2 Theoretical background and hypothesis development

2.1 *Government intervention in the PVC market*

High-tech entrepreneurial companies are particularly exposed to financial constraints (Denis 2004). The technology-intensive nature of these companies and their frequent lack of a track record make it difficult for external investors to gauge ex-ante the potential of their investment projects and to monitor ex-post the decisions made by entrepreneurs (Hall 2002; Carpenter and Petersen 2002b). Furthermore, the most effective contractual mechanisms that are drafted to circumvent these information asymmetries are weakened by the intangibility of high-tech entrepreneurial companies' assets, which cannot be pledged as collateral to secure debt (Berger and Udell 1990).

A widely shared view in the entrepreneurial finance literature is that VC investors possess superior screening capabilities (Chan 1983) to more effectively address information asymmetries than traditional financial intermediaries (e.g., Gorman and Sahlman 1989; Sahlman 1990; Gompers and Lerner 2001; Denis 2004). The potential agency conflicts that are associated with information asymmetries between VC managers and entrepreneurs are mitigated by using monitoring and staging mechanisms (Gompers 1995; Kaplan and Stromberg 2001). However, notwithstanding VC investors' superior abilities to address information asymmetries, the entrepreneurial finance literature has shown that an *equity gap* remains for many entrepreneurial companies, especially companies in the earliest stages of development (Murray and Lott 1995; Lockett et al. 2002; Kelly 2011). Furthermore, VC investors may be affected by "herding" attitudes that are typical of institutional investors (Devenow and Welch 1996) and concentrate on only a few industries that are deemed to have the highest growth potential (Lerner 2002) or only on core regions at the expense of peripheral, economically lagging regions (Harrison and Mason 1992; Sunley et al. 2005). Thus, despite the existence of VC firms, a

market failure in the financing of high-tech entrepreneurial companies can still justify government intervention.

Two main classes of mechanisms are available to government policy makers to address this market failure (Cumming, 2007). First, the government can intervene indirectly in the entrepreneurial finance market by defining the legal and fiscal environments where PVC firms operate. These indirect mechanisms include, for example, the regulation of pension funds (Gompers and Levin 1999), capital gains taxes (e.g., Keuschnigg and Nielsen 2001; Keuschnigg and Nielsen 2004) and bankruptcy laws (Armour and Cumming 2006). Second, governments can directly channel public financial resources to the VC industry. A significant concern regarding this type of intervention is that direct government investments will be counterproductive if they substitute for (i.e., crowd out) private investment (Gilson 2003; Leleux and Surlemont 2003). Many studies have thus attempted to evaluate whether government investments in the VC industry have a positive or negative impact (i.e., crowding-in compared with the crowding-out effect) on the total amount of VC funds that are raised from a macro perspective (i.e., countrywide or regional). These studies have found mixed evidence. The findings in Armour and Cumming (2006) and Cumming and Macintosh (2006) are consistent with a negative effect in Europe and Canada, respectively. Conversely, Jeng and Wells (2000), Leleux and Surlemont (2003), del-Palacio et al. (2012) and Brander et al. (2015) show that government investments positively affect the development of the VC industry.

It is notable that there is considerable variety in the type of allocations of government financial resources in the VC industry (Colombo et al. 2014), ranging from the provision of public funding to PVC funds (often termed as “hybrid funds”, e.g., Jääskeläinen et al. 2007) where the government acts as a limited partner and the general partner is a professional private fund manager, to VC funds that are owned and managed by a governmental entity (according to the definition of GVC that is used in this study). Regarding hybrid funds, evidence from the Australian Innovation Investment Fund (IIF) program suggests improved performance of the funded companies in terms of R&D, patents, time to initial public offering and market capitalization (Cumming 2007; Cumming and Johan 2014). In

Europe, a relevant example of joint public/private ownership in privately managed VC funds is the European Investment Fund (Buzzacchi et al. 2013). The effectiveness of this fund has not been thoroughly evaluated concerning the impact on investee firm performance and on stimulating the aggregate pool of PVC investments.

In contrast, the GVC funds that are owned and managed by a governmental entity are relatively diffused in Europe, but several examples can also be found elsewhere, such as the Korea Development Bank and Canada's Business Development Bank. Evidence from recent contributions suggests a negligible impact of the "go it alone" strategy of GVC on the performance of investee companies, in terms of exits (Cumming et al. 2014), sales and employee growth (Grilli and Murtinu 2014) and productivity (Alperovych et al. 2015). However, when GVC co-invests with PVC portfolio companies experience better performance concerning innovation (Bertoni and Tykvovà 2015) and sales growth (Grilli and Murtinu 2014; 2015). Finally, Brander et al. (2015) distinguish among government-owned VC (i.e., VC funds that are fully controlled by the government) and government-supported VC (i.e., VC funds that are only partially controlled by the government). They find that government-supported VC performs better than government-owned VC in terms of a portfolio company's total funding and successful exit.

In summary, the prior literature suggests the following: 1) the effect of direct government investment schemes in stimulating PVC investments is mixed, and 2) the value that is added by GVC on investee company performance is limited, particularly when GVC firms invest alone. However, we argue that entrepreneurial companies could benefit from GVC though a mechanism that until now has not been explored in the literature, i.e. GVC may be effective in facilitating entrepreneurial companies' access to PVC because of a certification effect. This certification effect may be the main source of value that is added by GVC.

2.2 *Hypotheses development*

According to the *certification hypothesis* (Lerner 2002, p. F77), the selective provision of GVC can certify the potential of an entrepreneurial company to PVC investors and increase the probability that the entrepreneurial company can raise capital. This effect is particularly valuable for entrepreneurial companies. Mature companies are likely to have the opportunity to convey information regarding their quality to uninformed third parties through other means (such as through patenting and successful new product development). In contrast, entrepreneurial companies are new to the market, lack a track record, and are thus subject to higher information asymmetries. In the context of high information asymmetries and few signals regarding an entrepreneurial company's quality, a PVC firm can use a company's receipt of a positive evaluation (i.e., a "stamp of approval", Lerner, 2002) from a GVC firm as a screening device in selecting companies for its own portfolio. Hall and Hofer (1993) have shown that PVC firms use third-party evaluations to improve decision making when screening proposals.

A necessary condition for receipt of GVC to be used as screening device by PVC firms is that the investment decisions of the government's officials in charge of evaluating investment proposals are not random (Takalo and Tanayama 2010) and that selected companies have the potential, if funded, to become good investment opportunities for PVC firms. There are several reasons to believe that GVC firms can identify promising companies when screening the investment proposals that are submitted to them. First, as Lerner (1999, p. 293) notes, it is not implausible that government officials can effectively screen such proposals. For instance, GVC investors affiliated to the Ministry of Innovation and Technology (such as BioM in Germany) may rely on specialists that have considerable insights into which technologies and companies are the most promising. Second, entrepreneurial companies can hesitate when asked to share sensitive information that is necessary to the evaluation of their investment projects with PVC investors because of appropriability concerns

(Ueda 2004).[1] However, GVC investors do not represent the same appropriability threat, which lowers information asymmetries and facilitates the GVC evaluation process (for a similar argument concerning selective R&D subsidies, see Colombo et al. 2012). Finally, GVC investors may be more motivated to screen investment projects than PVC investors because of free-riding problems. PVC investors may be reluctant to engage in costly screening activities when other private investors may also benefit from their efforts. In this respect, extant evidence suggests that GVC investors put more effort in screening proposals than private investors. In a survey of European VC investors, GVC investors claim that they spend more time evaluating proposals and selecting targets for investments than PVC investors (Luukkonen et al. 2011).

Thus, companies that successfully pass through GVC screening are "certified" and should have better chances to attract PVC investment. Although the existing literature does not directly address GVC's certification role, the literature on R&D subsidies provides empirical support that the receipt of R&D subsidies increases an entrepreneurial company's probability of receiving external financing in the future. Lerner (1999) shows that the companies that received Small Business Innovation Research (SBIR) awards in the U.S. are more likely to receive PVC than a matched sample of companies that have not received an SBIR award. Feldman and Kelley (2006) find that the receipt of a government R&D subsidy by the U.S. Advanced Technology Program increased the funding from other sources. Using a Belgian dataset of SMEs, Meuleman and De Maeseneire (2012) show that obtaining an R&D subsidy results in SMEs' improved access to long-term debt.

Regarding GVC, we may expect a similar certification effect. Government officials may be even more selective in providing GVC funding than subsidies. It is in the interest of GVC firms to select

[1] This problem is particularly relevant in the context of corporate VC (Dushnitsky and Lenox 2005; Katila et al. 2008).

recipients that can generate high investment returns in the future. This is not necessarily the case for subsidies that are typically channeled through grants (Brander et al. 2015).[2] We therefore posit the following research hypothesis regarding the certification role of GVC (Hypothesis 1).

Hypothesis 1: *The receipt of GVC increases the likelihood that a high-tech entrepreneurial company will receive PVC.*

Hypothesis 1 is silent regarding the potential success of the PVC investments that originated from GVC certification. In what follows, we argue that the potential success of PVC investments in companies selected by GVC (i.e., certified companies) may be higher than the potential success of PVC investments in non GVC-backed companies. First, the previous discussion on the screening abilities of GVC suggests that GVC firms may be able and have incentives to select promising entrepreneurial companies. Second, entrepreneurial companies that receive both GVC and PVC are subject to a double-screening process where they are required to meet the investment criteria of both GVC and PVC. Brander et al. (2015) discuss the idea that an entrepreneurial company that passes the screening that is imposed by more VC investors – GVC and PVC – is likely to be a more promising company. Cumming et al. (2014) suggest that investors with diverse backgrounds (which is expected among GVC and PVC investors) exercise different types of expertise to conduct more effective due diligence. Thus, PVC investments in GVC-backed companies should have, ceteris paribus, a relatively higher potential to be successful than PVC investments in non-GVC-backed companies.

[2] For example, the SBIR receives neither equity nor debt from the grantee in return for the subsidy (see, e.g., Gans and Stern, 2003).

The receipt of a second round of PVC financing can be considered as preliminary evidence of this potential.[3] PVC investors periodically evaluate the potential of their portfolio companies by staging capital infusions. This staging mechanism is used by PVC investors to gather information and monitor the progress of their investments, maintaining the option to abandon if they learn negative information about future prospects. After an initial capital infusion, PVC investors acquire information regarding the management team, the product and the market of the portfolio company (Ferrary 2010). If negative information concerning the company's potential is observed, a second round of financing is less likely (Gompers 1995; Tian 2011). Thus, portfolio companies are likely to receive follow-up funding only if their prospects remain promising. If companies that have received the double screening of GVC and PVC have higher potential to be successful than companies that passed only the screening of PVC, they should have a higher likelihood to receive a second round of PVC. Thus, we posit Hypothesis 2.

Hypothesis 2*: Conditional on the receipt of a first round of PVC, high-tech entrepreneurial companies that are originally selected by GVC have a higher likelihood to receive a second round of PVC than high-tech entrepreneurial companies that were not originally selected by GVC.*

Eventually, high-potential entrepreneurial companies are more likely to undergo a successful PVC exit through an initial public offering or sale to another company (e.g., Lerner 1994a; Gompers 1996). These exit modes allow PVC investors to collect capital gains from their investments and

[3] We acknowledge the possibility that PVC investors may invest in a second round not necessarily because they find the company particularly promising but for other reasons, such as preemption rights and the rights of first refusal that are stipulated by contract (see, e.g., Burchardt et al. 2014). However, although the presence of a second round of PVC is not a direct measure of investment success, we believe it is correlated with it. In fact, the survival to additional stages of funding is considered in the literature as preliminary evidence of investment success, particularly when the venture is still at an early stage and is not ready to be listed or acquired (Hochberg et al. 2007).

provide higher profits than other exit routes, such as buybacks, secondary sales and write-offs (Cumming and Johan 2008). If entrepreneurial companies that went through the double screening of GVC and PVC are more promising (Cumming et al. 2014; Brander et al. 2015), they should be more likely to have a successful exit than other PVC-backed companies. Thus, we state Hypothesis 3 as follows.

Hypothesis 3*: Conditional on the receipt of a first round of PVC, high-tech entrepreneurial companies that are originally selected by GVC have a higher likelihood to have a successful exit than high-tech entrepreneurial companies that were not originally selected by GVC.*

We are aware that there are several arguments against the idea that government officials have screening skills. The public finance literature has emphasized that government officials may frequently be influenced by political interests rather than social interests (Peltzman 1976; Becker 1983). For this reason, there may be some distortions in the process of selecting entrepreneurial companies and managing a GVC firm. Furthermore, it is questionable whether GVC managers have the necessary skills and investment experience to select the most promising projects. In particular, if GVC investments are directed to early-stage entrepreneurial companies that operate in industries that are characterized by higher information asymmetries (Colombo et al. 2015), it is particularly difficult to "pick winners" (Baum and Silverman 2004). Finally, GVC managers typically work under incentives that are not directly linked to investment performance (Leleux and Surlemont 2003; Armour and Cumming 2006). These arguments support the view that the receipt of GVC is not linked to an entrepreneurial venture's potential because a GVC manager's incentives and screening abilities are inadequate.

3 Data, sample selection and variables

3.1 *Data and sample selection*

We test our hypotheses on a sample of high-tech entrepreneurial companies that is extracted from the VICO dataset, which was developed in the framework of the VICO project (7th Framework Program of the European Commission, http://www.vicoproject.org). The VICO dataset is a unified, longitudinal, cross-country and cross-sector dataset that focuses on European high-tech entrepreneurial companies. These companies were independent at their founding (i.e., owner-managed) and operate in the following high-tech sectors: Internet, TLC, software, ICT manufacturing, biotech and pharmaceuticals, and other high-tech manufacturing and services. These companies are located in seven European countries, namely, Belgium, Finland, France, Germany, Italy, Spain and the United Kingdom.

The VICO dataset includes 759 VC-backed entrepreneurial companies that received their first infusion of VC in or after 1994; this dataset also includes approximately 8,000 non-VC-backed but "potentially investable" entrepreneurial companies (Bertoni and Martì Pellon 2011). For each company, the VICO dataset collects information regarding its founding year, industry of operation, country, accounting data, patenting activity and status (liquidation, listings and acquisitions) as of 2010.[4] For VC-backed entrepreneurial companies, the VICO dataset tracks information on all the investment rounds received since 1994, including the year, the amount received and the identity of the VC investor. The VICO dataset follows the criterion that has been adopted by most popular commercial databases (such as ThomsonOne), which classify VC firms by the diverse nature of the management company that is responsible for the investing process (i.e., the general partner). It is therefore possible to distinguish GVC firms from PVC firms in our dataset. GVC firms are VC firms that are managed by a company owned by a governmental entity. PVC firms are either independent,

[4] All of this information was collected by using a variety of commercial and proprietary sources. For the list of sources that were used in the data collection process, see Bertoni and Martì Pellon (2011).

"U.S.-style" VC firms or VC firms whose parent companies are either financial (such as banks) or non-financial corporations.

To select the sample for our analysis, we focus on 183 VICO entrepreneurial companies that received their first rounds of funding from a GVC firm. We refer to these companies as GVC-backed companies.[5] The 183 GVC-backed companies received their first round of investment from a total of 81 different GVC firms that operate in the seven countries that are included in the VICO database. As our control group, we use 8,094 VICO companies that did not receive GVC in their first round of VC investment.[6] Most of these companies have never received GVC. However, companies that received GVC after an initial round of investment from PVC are also considered part of the control group, but the observations after the receipt of GVC are excluded.[7] GVC-backed and control group companies are observed from 1993 (or from their inception if they were founded after 1993) to 2010 (or listing, acquisition or liquidation year, if applicable).

Table 1 shows the distribution of GVC-backed and control group companies according to industry, country and founding period. The distributions of the two groups of companies significantly differ along these three dimensions (the chi-square tests on the differences in the distribution are, as follows: $\chi^2(5)=50.4$, $\chi^2(6)=34.0$ and $\chi^2(2)=5.9$, for industry, country and founding period, respectively).

[Insert Table 1 about here]

Table 2 shows the distribution of the sample companies according to the year that they received their first round of GVC. The 183 GVC-backed companies received a first round of GVC between 1994 and 2004, and the peak in such financing occurred in 2000. In our sample, 565 companies

[5] This sample includes 71 entrepreneurial companies that received GVC and PVC in the same year. In section 4.3, we discuss whether and how the inclusion of these companies may affect the results from econometric estimates.
[6] Unfortunately, our data do not track investments that are provided by individuals (e.g., business angels). Therefore, we are unable to consider the effect of angel financing in our analysis.
[7] As a robustness check, we eliminated these companies from our sample. The results are unchanged and available from the authors upon request.

(considering both GVC-backed and control group companies) received PVC funding. These companies received their first round of PVC between 1994 and 2007, with again a peak in 2000. The clustering of first VC investments near 2000 can be explained by the dot-com bubble that peaked at that time.

[Insert Table 2 about here]

GVC-backed companies received between one and six rounds of GVC between 1994 and 2010, with an average of 1.6 rounds. The large majority of these companies (62.8%) received only a first round of GVC, and 22.9% received two rounds. The average capital injection per round is equal to € 493,226 (the median is € 88,313). In total, the 81 GVC firms injected more than € 144 million in the 183 sample companies during our observation period. The GVC-backed companies that attracted PVC received between one and eight rounds of PVC, with an average of 1.8 rounds per company (this average is not significantly different from the average number of rounds of PVC financing that were received by the PVC-backed companies in the control group, i.e., 1.7).

3.2 *Dependent variables*

The dependent variables of our empirical analysis are three dummy variables, and they indicate events that occurred during the entrepreneurial companies' lives. $PVC_{i,t}$ switches from 0 to 1 in the year when company *i* received a first round of PVC. $PVCsecond_{i,t}$ switches from 0 to 1 in the year when company *i* received a second round of PVC by at least one of the PVC investors that participated in the first round. Finally, $SuccessfulExit_{i,t}$ switches from 0 to 1 in the year when company *i* was either listed or acquired by another company.[8] These three variables are used to estimate the companies' likelihood of receiving a first round of PVC (Hypothesis 1), receiving a second round of PVC (Hypothesis 2), and having a successful exit (Hypothesis 3), respectively. The probability of receiving

[8] The results are similar if we consider the listing and the acquisition of the company separately.

a second round of PVC and having a successful exit are considered conditioned on the receipt of a first round of PVC.

In Panel A of Table 3, we report the distribution of GVC-backed and control group companies by receipt of a first round of PVC. Of the 183 GVC-backed companies, 94 (51.4%) received PVC. Of the 8,094 control group companies, 471 (5.8%) received PVC. A χ^2 test indicates that the distribution of GVC-backed companies is significantly different from the distribution of the overall sample at the 1% level.

In Panel B of Table 3, we restrict the sample to the 94 GVC-backed and 471 control group companies that received at least one round of PVC. Of the 94 PVC investments in GVC-backed companies, PVC investors followed with a second financing round in 38.3% of the cases (36). The companies were listed or acquired in 35.1% (33) of cases. Regarding the 471 PVC investments in the control group companies, we find similar shares (34.2% received a second financing round, and 25.3% were listed or acquired). There are no significant differences in the distribution of GVC-backed and control group companies at conventional confidence levels ($\chi(1)=0.4$ for the second round of PVC, and $\chi(1)=2.7$ for an investee company's successful exit).

Companies that did not receive PVC are shown in Panel C of Table 3. Of the 89 GVC-backed companies, 13 (14.6%) were eventually listed or acquired without the intervention of a PVC investor. In the control group, the frequency is significantly smaller ($\chi(1)=15.3$, p-value<1%): only 391 of the 7,623 companies (5.1%) were listed or acquired. However, the GVC-backed companies that did not receive PVC were listed and acquired at a significantly lower rate than the GVC-backed companies that received PVC ($\chi^2(1)=4.5$, p-value<5%).

[Insert Table 3 about here]

As explained in section 4.2 below, the timing of events is also important for our purposes. Table 4 shows that GVC-backed companies in our sample are, on average, 2.3 years old when they received their first round of GVC. PVC financing (if any) occurs an average of 0.9 years after receipt of the

first round of GVC. On average, GVC-backed companies are 3.2 years old when they receive their first round of PVC, whereas the control group companies are 2.3 years old. A t-test shows that this difference is significant at the 1% level. The companies that receive a second round of PVC obtain it approximately two years after the first round. The time between the first round of PVC and successful exit (when there is a successful exit) is approximately five years (the t-tests do not show significant differences between the GVC-backed and control group companies in this regard).

[Insert Table 4 about here]

3.3 *Independent variables*

Our main independent variable is the dummy variable $GVC_{i,t}$ that switches from 0 to 1 in the year when company *i* received its first round of GVC. We lag the variable by one year to reduce the risk that inverse causality drives our results. In our model, we also add the cumulative amount that is invested by GVC in company *i* until *t*, lagged by one year, in millions of euros ($GVCamount_{i,t-1}$). Entrepreneurial companies that receive higher amounts of GVC can invest more in their development. These companies are therefore closer to a successful exit event and are more attractive to PVC investors that are moved by "window-dressing" behavior (Lerner 1994a).

Concerning company-level characteristics, we control for the age ($Age_{i,t}$), size, which is measured by the logarithm of total assets ($TotalAssets_{i,t}$), and the stock of the patents that are granted ($Patents_{i,t}$), cumulated and depreciated over time with a yearly depreciation coefficient of 0.85 (see Griliches 1992 and Bertoni and Tykvovà 2015 for a similar approach). In addition to important measures of innovative performance, patents are fundamental to high-tech entrepreneurial ventures based on their signaling value to external investors (Audretsch et al. 2012; Hoenen et al. 2014). We lag $TotalAssets_{i,t}$ and $Patents_{i,t}$ by one year to reduce the risk of reverse causality. We control for successful exit opportunities by considering the logarithm of the number of companies that were listed in Europe in

the previous year ($NumberIPO_{t-1}$, source: ThomsonOne).[9] We also include dummy variables related to an entrepreneurial company's country, industry of operation and time period (before 1999, during the Internet bubble of 1999-2000, and after 2000).

The aforementioned variables are included throughout the entire analysis. When modeling the probability of receiving a first round of PVC (Hypothesis 1), we also consider the availability of PVC funds at time *t*, measured as PVC fundraising in Europe each year in billions of euros ($PVCfundraising_t$, source: ThomsonOne). We lag the variable by two years to account for the delays between fundraising and the actual availability of funds on the market. In the models regarding the receipt of a second round of PVC and successful exit (Hypotheses 2 and 3, respectively), we control for the amount that is invested by PVC (Lerner 1994a) and PVC experience (Gompers et al. 2009). We measure the former with $PVCamount_{i,t-1}$, the lag of the cumulative amount invested by PVC in company *i* until time *t*, in millions of euros. With respect to the latter, $PVCexperience_{i,t}$ measures the average years of experience of the PVC investors that are involved in the investment. Years of experience are measured as the number of years since the founding of the PVC firm (see Hochberg et al. 2007 for a similar approach). In cases involving corporate and bank-affiliated VC – where a VC firm is not created and funds are directly managed by the parent company – we compute PVC experience as the number of years since the first PVC investment. Controlling for PVC experience helps us rule out the alternative explanation that GVC attracts PVC investors that are more experienced and are more likely to help target companies have a successful exit.

Finally, we include the availability of GVC when necessary, which is measured as the GVC fundraising in each entrepreneurial company's country *c* in millions of euros lagged by two years ($GVCfundraising_{c,t-2}$, source: ThomsonOne). Table 5 shows the variables' summary statistics and the

[9] The results are unchanged when we consider the yearly number of mergers and acquisitions in each country (source: Thomson One).

correlation matrix. In the few cases where the correlations among the variables are high, we monitor the variance inflation factor to exclude multi-collinearity.

[Insert Table 5 about here]

4 Event history analysis after matching

4.1 *Matching algorithm*

Our hypotheses suggest a causal positive relation between the receipt of GVC and an entrepreneurial venture's likelihood of receiving a first round of PVC, receiving a second round of PVC or having a successful exit. Methodologically, we must pay particular attention to the endogeneity of $GVC_{i,t}$. Some companies' characteristics may affect both the probability of being GVC-backed and the probability of receiving a first round of PVC (and for PVC-backed companies, the likelihood of receiving a second round of PVC or having a successful exit). For example, GVC firms may select promising companies that would receive a PVC investment or have a successful exit even in the absence of GVC. If this proposition is true, we may find that the receipt of GVC has a positive effect on the probability of receiving a first round of PVC, even if there is no certification at work. Similarly, if we find that PVC investments in GVC-backed companies are successful, we may incur the risk of erroneously attributing a positive screening and certification function to GVC when PVC would have selected these companies anyway.

One way to address this endogeneity is to use a matching procedure to select an appropriate counterfactual, a method that is commonly undertaken in the VC literature (e.g., Megginson and Weiss 1991; Engel and Keilbach 2007; Croce et al. 2013). In particular, we match our sample of GVC-backed entrepreneurial companies to non-GVC-backed entrepreneurial companies with similar observable characteristics. The implicit assumption that is made is that matched companies have the same characteristics as GVC-backed companies (including the probability of receiving a first round of PVC, a second round of PVC or having a successful exit), and the only difference is that the

matched companies did not receive a GVC investment. Under this assumption, any positive effect of $GVC_{i,t}$ can be credited to the screening and certification effects of GVC.

Following Lerner (1999), we consider the 183 GVC-backed companies in the year when they received their first round of GVC and all the company-year observations from the control group companies. We estimate a logit model in which the dependent variable is the likelihood that the entrepreneurial companies receive GVC in a given year. The independent variables include the entrepreneurial company's age ($Age_{i,t}$), size ($TotalAssets_{i,t-1}$) and number of patents ($Patents_{i,t-1}$) from the previous year in addition to country and industry dummies (see Croce et al. 2013 for a similar choice of matching variables in a similar context). We also include the availability of GVC ($GVCfundraising_{c,t-2}$). Based on the predicted probability that is estimated by the logit model (pseudo R^2=0.14), we compute a propensity score. We use the propensity score and the age of the entrepreneurial company as matching variables to select – for every GVC-backed company in the year of the GVC investment – the five most similar company-year observations (nearest neighbors) in the control group. We use the Mahalanobis distance as our distance measure.[10] This method produces a matched sample of 788 "twins" of the 183 GVC-backed companies.

Because of the matching procedure, the distribution of the GVC-backed companies is not significantly different from the distribution of the matched companies in terms of industry, country and founding periods ($\chi^2(5)$=1.1, $\chi^2(6)$=3.9 and $\chi^2(2)$=3.3, respectively). We tested the balancing of the matching regarding the characteristics of the companies measured by continuous variables using t-tests. The GVC-backed companies and their matched peers were not different at the matching time

[10] This matching procedure is a combination of propensity score matching and Mahalanobis distance. This procedure allows us to minimize the discrepancy along the propensity score (which condenses all the independent variables in a single construct) and the single variables that are particularly important for the model, such as $Age_{i,t}$ in this case (Rosenbaum and Rubin 1985). The results are qualitatively similar when using other matching criteria (see section 4.3).

for average age, size and innovativeness and were located in countries with similar GVC availability, as shown in Table 6.

[Insert Table 6 about here]

4.2 *Event-history model*

We analyze the sample of GVC-backed companies and their matched "twins" with a semi-parametric Cox event-history type model (Cox 1972) that has been extensively used in the VC context (see, e.g., Chang 2004; Giot and Schwienbacher 2007; Bertoni and Groh 2014).[11] Specifically, to test Hypothesis 1, we estimate the likelihood that the focal company will obtain its first round of PVC after t years from its founding, conditioned on not obtaining such financing up to t (i.e., the hazard rate of receiving a first round of PVC). The exposure time t is represented by the years since the company's founding and is therefore equal to the company's age ($Age_{i,t}$). We exclude from the analysis the company-year observations after liquidation, listing and acquisition.

We then estimate the likelihood that a PVC-backed company will receive a second round of PVC (Hypothesis 2), computed t years after the first round of PVC, conditioned on not receiving such funding up to t (i.e., the hazard rate of receiving a second round of PVC) and the likelihood of being listed or acquired (Hypothesis 3) computed t years after the first round of PVC, conditioned on not being listed or acquired up to t (i.e., the hazard rate of successful exit). These two models are defined only for the GVC-backed companies and matched "twins" that received a first round of PVC, and

[11] Although probit or logit models allow us to predict whether an event will occur, event-history models also consider when an event will occur. Event-history models estimate the hazard rate, i.e., the probability that an event will occur at a certain time, which allows us to better exploit the longitudinal nature of our dataset. The Cox model is a flexible type of event-history model because it does not require the distribution of the time dependence of the hazard rates to be specified. For comparison purposes, we use probit models instead of the Cox event-history models. The results are unchanged and are available upon request.

exposure time *t* is represented by the years since this financing event. We exclude from the analysis the company-year observations that follow a liquidation event.[12]

4.3 *Results regarding the receipt of a first round of PVC*

Table 7 presents the results of the event-history analysis relative to the probability of receiving a first round of PVC (Hypothesis 1). The model in column I only accounts for the control variables. In column II, we add the main independent variable, i.e., $GVC_{i,t-1}$. In column III, we add the amount invested by GVC, $GVCamount_{i,t-1}$. The final specification is presented in column IV, and includes both $GVC_{i,t}$ and $GVCamount_{i,t-1}$.

The control variables' coefficients are similar across the models. $TotalAssets_{i,t-1}$ and $Patents_{i,t-1}$ have positive and significant coefficients (at least at the 5% and 1% levels, respectively). Larger and more innovative companies are more likely to receive PVC. The hazard rate is also higher when the external conditions are favorable to PVC investments in terms of fundraising and exit opportunities, because in all models, the coefficients of $PVCfundraising_{t-2}$ and $NumberIPO_{t-1}$ are both positive and significant at the 1% and 10% levels, respectively.

Our main independent variable, $GVC_{i,t-1}$, has a positive and significant (at the 1% level) coefficient in all models that include it. $GVCamount_{i,t-1}$ is significant in column III but is not significant when it is included with $GVC_{i,t-1}$, such as in column IV. According to the full-fledged model that is presented in column IV, the positive effect of GVC on the probability of receiving a

[12] Our empirical setting follows a multi-stage selection process. Companies are included in our models of the second round of PVC and successful exit only if they are first selected by PVC. In a multi-stage model, the past history of the process may affect its future evolution even after the current stage has been accounted for (Balakrishnan and Rao 2004). Neglecting the past history can therefore create some bias in the estimates of the probability of subsequent events. As a robustness check, we use the two-stage approach from Eckhardt et al. (2006) to control for this bias. The results are unchanged and available from the authors upon request.

first round of PVC is economically substantial. The hazard ratio of $GVC_{i,t-1}$ is 3.36 ($e^{1.213}$) and implies that the GVC-backed companies have a probability of receiving a first round of PVC that is more than three times the corresponding probability for the matched companies. This increased likelihood of receiving a first round of PVC financing is not because of the amount invested by GVC and therefore, is not a consequence of the "window-dressing" behavior of PVC. These results support Hypothesis 1.[13]

[Insert Table 7 about here]

In the Table 8, we present some robustness checks of our results. First, we test the robustness of our matching procedure by using different counterfactuals for our GVC-backed companies (columns I-IV). The results remain substantially unchanged when selecting seven or three "twins" for each GVC-backed company from the control group as alternative counterfactuals instead of the five "twins" that are used in our main tests. The results are also robust when using as a counterfactual a "pure" propensity score matching or a random sample from the control group.

Second, we exclude the cases where GVC and PVC investing begins in the same entrepreneurial company in the same year (71 cases). In the estimates that are reported in Table 7, we implicitly assumed that the companies that receive both PVC and GVC in the first round are not subject to GVC certification. In the year of a co-investment, the coefficient of the lagged variable $GVC_{i,t-1}$ is equal to 0, whereas the dependent variable PVC_t equals 1 (and the following years are excluded from the event-history analysis). This choice is cautious because it is unclear whether these GVC-backed companies were originally selected by GVC or by PVC; therefore, it is questionable to ascribe these

[13] We also tested Hypothesis 1 separately for different types of PVC, such as independent VC, corporate VC and bank-affiliated VC. The coefficient of $GVC_{i,t-1}$ is positive and significant in the models for independent and corporate VC investors, which indicates that the receipt of GVC certifies entrepreneurial ventures to these two types of private VC. A possible interpretation of these results (available from the authors upon request) is that the companies in a GVC firm's portfolio are interesting to strategic investors (corporate VC firms), because of the technology that they develop, and to financial investors (independent VC firms) for their potential financial results.

investments to GVC certification. However, this choice may result in a downwardly biased estimate of a GVC firm's effect on a company's likelihood of receiving a first round of PVC. When we exclude co-investments from the analysis (see column V in Table 8), the coefficient of $GVC_{i,t-1}$ is positive and significant at the 1% level, and the hazard ratio of the variable is higher and equal to 12.83 ($e^{2.552}$).

Third, we further restrict our control sample by focusing only on the entrepreneurial companies that have actively sought external equity financing (see column VI in Table 8). These companies are more likely to be financed by both PVC and GVC. However, if the proportion of companies that are actively seeking external equity financing is different between the GVC-backed and the matched sample, a possible bias in the estimated coefficients can arise. We address this potential source of bias by excluding the companies that never sought PVC. This information was collected through an online survey that was administered to the VICO companies in 2010. The companies were asked whether they had "ever sought equity financing from sources other than founders, their family members and friends." Unfortunately, the response rate was low, and only 140 companies answered "yes" to this question. Despite the low number of observations that are available for the analysis, our results still indicate that the presence of GVC positively affects companies' likelihood of receiving a first round of PVC (at the 5% level).

[Insert Table 8 about here]

Finally, we run additional robustness checks, whose results are omitted here for synthesis. First, to account for other factors that may impact the probability of receiving PVC, we consider a company's leverage, sales growth and profitability (ROE) as additional control variables in our model. These data are available for only a subset of companies. However, none of these additional controls is significant in our models, and they do not affect the significance of our main independent variable, $GVC_{i,t-1}$. Second, we control for the number of rounds of GVC that the target company receives, because the effectiveness of the certification may be influenced by the fact that a company has received multiple rounds of GVC financing. However, the results indicate that this is not the case in our sample. Third, a possible alternative explanation for our results is that GVC increases

entrepreneurial companies' survival chances during the seed stage (Manigart et al. 2002). If this explanation is accurate, then GVC-backed entrepreneurial companies are exposed to the risk of receiving PVC longer than non-GVC-backed companies and are therefore more likely to receive a first round of PVC. To rule out this alternative explanation, we test the effects of GVC on an entrepreneurial venture's likelihood of bankruptcy. Our results indicate that GVC does not reduce an entrepreneurial company's likelihood of bankruptcy, which is consistent with the findings from Manigart et al. (2002) in Belgium. Therefore, the GVC-backed companies are not exposed to the risk of receiving PVC financing for a longer time than the matched companies.

4.4 *Results regarding the receipt of a second round of PVC and successful exit*

In this section, we consider what occurs after the initial financing round of PVC. Columns I and II of Table 9 present the results of event-history analysis for the receipt of a second round of PVC (Hypothesis 2) and a successful exit (Hypothesis 3), respectively, for the GVC-backed and matched companies that received a first round of PVC.

In column I, the hazard rate of receiving a second round of PVC is positively affected by the amount of capital injections and the experience of PVC investors, because both $PVCamount_{i,t-1}$ and $PVCexperience_{i,t-1}$ have positive and significant coefficients (at the 10% and 1% levels, respectively). The other control variables are not significant. Similar to the findings of previous studies (Hoenen et al. 2014), the variables that explain an entrepreneurial company's probability of receiving a first round of PVC (namely, company size and patenting activity) do not influence the probability of receiving a second round. Nevertheless, our variable of interest, $GVC_{i,t-1}$, is slightly significant in the model. The coefficient is significant at the 10% level and indicates that on an annual basis, the companies that were backed by GVC before they received their PVC investment are 4.17 ($e^{1.427}$) times more likely than other companies to receive a second round of PVC. This evidence is consistent with Hypothesis 2, although the statistical significance is relatively weak.

Concerning successful exit, column II of Table 9 shows that an entrepreneurial company's hazard rate of being listed or acquired is positively influenced by its patenting activity ($Patents_{i,t-1}$, significant at the 5% level) and the presence of exit opportunities on the market ($NumberIPO_{t-1}$, significant at the 10% level). $GVCamount_{i,t-1}$ has a coefficient that is positive and significant (at the 10% level) and suggests that the PVC-backed companies that received more funds from GVC investors are more likely to have a successful exit. However, $GVC_{i,t-1}$ is not significant. The double screening process that is associated with GVC and PVC does not lead to greater success. Therefore, we do not find support for Hypothesis 3 in these results.

[Insert Table 9 about here]

We test the robustness of our models regarding the receipt of a second round of PVC and a successful exit by including additional controls. First, we add the number of VC investors that participated in each first PVC round, lagged by one year. In this way, we control for the fact that syndicated deals may be more successful than standalone deals because of the value of a "second opinion" (Lerner 1994b; Brander et al. 2002; Manigart et al. 2006). If PVC investors tend to invest in GVC-backed companies with larger syndicates, then the positive effect of GVC on the probability of receiving a second round of PVC, which is reported in Table 9, may be driven by the better screening function that is associated with larger PVC syndicates, not the double screening of GVC and PVC. Second, we add the age of the investee companies at the time of the first PVC investment. We consider the possibility that companies that receive PVC investments at different stages of their lives may have different likelihoods of reaching the second round of PVC or of being listed or acquired. Third, we control for the number of rounds of PVC that the target company receives in our model of successful exit, because the literature suggests that this number may influence investment performance (Tian 2011). None of these additional controls are significant, and they do not influence the results of the analysis. Fourth, we control for the experience of GVC investors – by using a similar metric to the metric used for PVC – to address the potential heterogeneity in the screening skills of the GVC investors in our sample. Finally, we isolate the effect of PVC-GVC co-investments in the

same year by including a dummy variable that equals 1 in the year of the co-investment and in all following years and is 0 otherwise. In these last two robustness checks regarding investor experience and co-investments, $GVC_{i,t-1}$ becomes insignificant in the model of the second round of PVC.[14]

5 "What if" analysis with an endogenous switching regression model

5.1 *Switching regression model with endogenous switching*

The main drawback of the matching-based analysis that was presented in the previous section is that the selection of "twins" is based on only observable variables (Smith and Todd 2005). Unobservable factors, such as the quality of the business plan or the entrepreneurial capital of the companies, are not considered. Firms that received GVC funding may be more likely to receive PVC than their matched twins because of these unobservable factors. If this is true and if the endogeneity of GVC treatment ($GVC_{i,t}$) is also due to non-observable characteristics, then the matching procedure is insufficient to address it, and our conclusions on our hypotheses may be erroneous.

The endogenous switching regression model (see Chemmanur et al. 2011, for an application in the VC context) allows us to better control for the unobservable characteristics that affect the probability that an entrepreneurial company will receive GVC financing and the probability that the company will receive PVC financing, obtain a second round of PVC and have a successful exit.

We rely on the entire sample of 183 GVC-backed and 8,094 control group companies (described in section 2.1) in the endogenous switching regression model, which consists of two stages (Heckman 1979; Maddala 1983). The first stage is a probit model for GVC selection, where the dependent variable is $GVC_{i,t-1}$, and the independent variables are $PVCfundraising_{t-2}$, $GVCfundraising_{c,t-1}$, $Age_{t,i}$, $TotalAssets_{i,t-1}$, $Patents_{i,t-1}$, and $NumberIPO_{t-1}$, as well as country, industry and period dummies. All

[14] The results of these additional robustness checks are omitted here for synthesis but are available from the authors upon request.

observations after the first receipt of GVC are excluded from this stage. In the second stage, we estimate the probabilities of receiving a first round of PVC (Hypothesis 1), receiving a second round of PVC (Hypothesis 2) or having a successful exit (Hypothesis 3) by using a probit specification with $PVC_{i,t}$, $PVCsecond_{i,t}$ and $SuccessfulExit_{i,t}$ as the dependent variables, respectively, and $PVCfundraising_{t-2}$, $Age_{t,i}$, $TotalAssets_{i,t-1}$, $Patents_{i,t-1}$, $NumberIPO_{t-1}$, and country, industry and period dummies as regressors.[15]

The endogenous switching regression model is characterized by the fact that the probabilities are estimated separately for GVC-backed and control group companies (the variable $GVCamount_{i,t-1}$ is added only for GVC-backed companies). To control for the unobservable characteristics that may affect the entrepreneurial company's probability of falling into one of these two subsamples (the GVC-backed or the control group), an inverse Mills ratio (*IMR*) is computed after the first stage and added to the regressors (see Fang 2005 for details regarding how to compute the IMR).[16]

$GVCfundraising_{c,t-1}$, which is included in the first step of the endogenous switching regression, is not included in the second step. This variable is likely to be correlated with the probability of receiving GVC (the higher the GVC fundraising in a given country the year before, the more likely it is for companies to receive this type of support). However, this variable is unlikely to be correlated with the probability of receiving PVC, receiving a second round of PVC or having a successful exit. For these reasons, the variable is used as an instrument to identify the model. The identification of the endogenous switching regression strongly depends on the strength of the instrument that is used (Maddala 1983). $GVCfundraising_{c,t-1}$ appears to be a reasonable instrumental variable here because it explains the exogenous variations in our endogenous variable, $GVC_{i,t-1}$ (Brander et al. 2015).

[15] Following the discussion provided in section 4.3, we exclude GVC-PVC co-investments from the analysis on the probabilities on receiving PVC in order to avoid overestimating the certification effect of GVC.

[16] Freedman and Sekhon (2010) indicate that the use of Heckman (1979) two-step method when the second stage is a probit model may create some biases in the estimated coefficients. As a robustness check, we repeated the analysis by using OLS in the second stage, instead of probit. Results hold and are available from the authors upon request.

The predicted probabilities of each event of interest (receipt of the first round of PVC, receipt of the second round of PVC or successful exit) from the second-stage estimates are used to conduct a "what if" analysis. Specifically, we estimate the probability of each event for the GVC-backed companies based on the coefficients of the control group regression (by using the data on GVC-backed companies). These probabilities correspond to what would have occurred if the GVC-backed companies had not received GVC investments. Similarly, we estimate the probability of each event for the control group companies based on the coefficients of the GVC-backed group regression (by using the control group data). Finally, we compare the estimated "what if" probabilities of the events of interest with the actual frequencies of these events.

5.2 *Results of the endogenous switching regression*

The results of the first stage of the endogenous switching regression model regarding the probability of receiving GVC are shown in column I of Table 10. The coefficient of $Age_{i,t}$ is negative and significant at the 1% level, whereas the coefficient of $GVCfundraising_{c,t-1}$ is positive and significant at the 5% level. Younger companies that operate in countries where GVC is more developed are more likely to receive GVC. This probability increases in periods of high exit opportunities, because the coefficient of $NumberIPO_{t-1}$ is also positive and significant at the 1% level.

[Insert Table 10 about here]

Columns II and III report the probit estimates regarding the likelihood that the GVC-backed and control group companies will receive a first round of PVC. In the sample of GVC-backed companies, the insignificant *IMR* suggests that GVC firms select companies whose unobservable characteristics do not make them more likely to receive PVC. The size of the company is the only observable characteristic that affects PVC decisions to invest in GVC-backed companies (the coefficient of $TotalAssets_{i,t-1}$ is positive and significant at the 1% level). Neither observable nor unobservable variables have particularly strong explanatory powers in PVC firms' decisions to invest in GVC-backed companies. A possible interpretation of this fact may be that PVC firms make this

decision by relying on the observation that the entrepreneurial company has received GVC. The results of the "what if" analysis that are shown in the next section help us verify whether the receipt of GVC positively affects the probability of receiving PVC (i.e., Hypothesis 1). In the control group, company size, age, the availability of PVC funds and exit opportunities play significant roles in the likelihood of receiving a first round of PVC (the coefficients of $TotalAssets_{i,t-1}$, $Age_{i,t}$, $PVCfundraising_{t-2}$ and $NumberIPO_{t-1}$ are significant at the 1% level). Furthermore, *IMR* is positive and significant at the 5% level and emphasizes that there are certain unobservable characteristics that make the control group companies (the companies not selected for GVC financing) more likely to receive a first round of PVC.

The results for the determinants of an entrepreneurial company's receipt of a second round of PVC are reported in columns IV and V. Younger and larger companies that received higher amounts from PVC investors are more likely to receive a second round of PVC in both the GVC-backed and the control groups ($Age_{i,t}$ is significant at the 1% level, $TotalAssets_{i,t-1}$ at the 5% level, and $PVCamount_{i,t-1}$ at least at the 5% level). In the GVC-backed group, the level of experience of the PVC investors ($PVCexperience_i$) is also significant at the 5% level. Moreover, GVC-backed companies have certain unobservable characteristics that make them more likely to reach a second round of PVC because *IMR* is positive and significant at the 5% level. This result is consistent with the fact that PVC investments in GVC-backed companies are associated with a greater likelihood of obtaining a second round of PVC based on the selection of GVC, which supports Hypothesis 2. A one standard deviation increase in *IMR* generates a threefold increase in the probability of receiving a second round of PVC.

Finally, columns VI and VII show the results concerning the probability of a successful exit. In the GVC-backed group, the coefficients of $Age_{i,t}$, $Patents_{i,t-1}$ and $GVCamount_{i,t-1}$ are all positive and significant at the 5% level. In the control group, $TotalAssets_{i,t-1}$ and $Patents_{i,t-1}$ present positive and significant coefficients at the 1% and 5% levels, respectively. Regarding the selection terms, *IMR* is not significant in the group of GVC-backed companies, which suggests that that PVC-backed

companies that are selected by GVC are as likely to be listed or acquired as purely PVC-backed companies. Therefore, we do not find support for Hypothesis 3. However, *IMR* is negative and significant at the 1% level in the control group, which indicates that companies not selected for GVC financing have certain unobservable characteristics that make them less likely to be listed or acquired. This result supports the view that GVC firms' screening abilities are valuable because GVC firms do not select companies that have an inferior likelihood of success.

5.3 *Results of the "what if" analysis*

Finally, we present the results of the "what if" analysis. Table 11 shows the estimated probabilities of the events of interest that are derived from the endogenous switching regressions shown above. For each event, we compare the estimated likelihood of the event for the GVC-backed companies if they had fallen into the control group with the actual frequency of the event. Similarly, we compare the estimated probability of the event for the control group companies if they had fallen into the GVC-backed group with the actual frequency of the event.

[Insert Table 11 about here]

Panel A of Table 11 shows that if the GVC-backed companies had not been backed by GVC, they would have had a lower probability of receiving a first round of PVC. Similarly, if the control group companies had received GVC funding, they would have had a higher probability of receiving a first round of PVC. Both of these differences are significant at the 1% level.[17] These results are consistent with the view that the treatment effect of GVC is non-negligible, when controlling for both the observable and unobservable characteristics that may affect the probability of the receipt of GVC and PVC. The receipt of GVC actually increases an entrepreneurial company's likelihood of receiving

[17] We repeat the exercise for subsets of observations for GVC-backed companies, depending on how much time had passed since GVC financing. The most significant differences emerge three and four years following GVC financing. Beyond that time horizon, the effect vanishes.

a first round of PVC, which is consistent with Hypothesis 1. The effect is economically substantial: GVC-backed companies are five times more likely to receive a first round of PVC than they would have been had they not received GVC. We ascribe this result to the certification effect of GVC.

For completeness, in Panels B and C of Table 11, we report the results of the "what if" analysis concerning PVC-backed companies. The "what if" analysis of the likelihood of receiving a second round of PVC or of being listed or acquired does not test Hypotheses 2 and 3. These hypotheses address the selection of GVC, whereas the differences between the estimated probability of the event of interest (i.e., a second PVC round or a successful exit) and its actual frequency must be interpreted as the treatment effect of GVC. The results shown in Panel B of Table 11 show that if GVC-backed companies had not been backed by GVC, they would have had the same probability of receiving a second round of PVC and vice-versa. Concerning successful exits, Panel C of Table 11 shows that if the GVC-backed companies had been part of the control group, nothing would have changed regarding their probabilities of being listed or acquired. However, if the control group companies were backed by GVC, they would have had a higher probability of having a successful exit, with a difference that is significant at the 10% level. Therefore, we find (weak) evidence of the positive treatment effect of GVC on PVC investment success. This effect may be because of the value that GVC adds.

6 Discussion and conclusions

In this paper, we test whether GVC investors can screen the market, select promising entrepreneurial companies and certify them to PVC investors. Our analysis is based on a European sample of 183 GVC-backed, high-tech entrepreneurial companies and a control group of 8,094 of their peers that were extracted from the VICO dataset.

The most important result of our paper is that receipt of GVC significantly increases an entrepreneurial company's likelihood of receiving PVC at least threefold. We interpret this result as evidence of the screening ability and certification effect of GVC in Europe. The receipt of GVC

reduces information asymmetries that typically affect high-tech entrepreneurial companies and facilitates their access to the PVC market. This result is robust to the alternative explanation that GVC-backed companies eventually would have been able to attract PVC without the intervention of GVC. We exclude this possibility by using a sound methodology that compares what actually occurred to companies after they received GVC with what would have occurred had these companies never received GVC.

The second important result is that PVC investments in GVC-backed companies are more likely to reach a second round of PVC than other PVC investments (even if the result has a weak statistical significance). This effect seems to be driven by the selection of GVC. Companies that completed the double screening selection processes of GVC and PVC seem to be worthy of receiving additional PVC financing. However, the two groups of companies have a similar likelihood of having a successful exit. Therefore, our analyses do not support the argument that the companies that were successfully screened by both GVC and PVC firms have a higher potential of resulting in successful PVC investments compared with the companies that were only selected by PVC firms. Nevertheless, we show that the entrepreneurial companies that are selected by GVC investors and then selected by PVC investors have at least the same potential to result in successful PVC investments as the companies that were directly selected by PVC investors.

Third, our methodology allows us to control for the fact that the probabilities of receiving a second round of PVC or having a successful exit can potentially be affected by the value that GVC adds after the initial provision of capital (i.e., a treatment effect in addition to the selection effect concerning GVC certification). The "what if analysis" indicates that GVC investment per se has a weakly significant positive treatment effect on the likelihood of a successful exit of PVC-backed companies. We interpret this result as evidence of a small overall effect of GVC value-adding activities on the performance of companies that received both PVC and GVC.

The results of this paper are significant for the GVC literature along several directions. First and most importantly, we provide support for the *certification hypothesis* that was advanced by Lerner

(2002) and until now, has never been explicitly tested for GVC despite its importance. Our results indicate that in Europe, PVC investors use the receipt of GVC as a screening device to select promising entrepreneurial companies, which is similar to what occurs for R&D subsidies (Meuleman and De Maeseneire 2012). Second, we offer preliminary evidence of the screening power of GVC. Researchers have been strongly skeptical of this power because of possible political distortions and the lack of adequate skills and incentives of GVC firms (Brander et al. 2008). Third, our results also concern the debate regarding GVC's effectiveness in supporting companies. The literature has shown that GVC investors provide limited value-enhancing services to the companies in their portfolios (Luukkonen et al. 2013) and consequently have a negligible treatment effect on company performance (Grilli and Murtinu 2014; Cumming et al. 2014; Bertoni and Tykvovà 2015; Brander et al. 2015; Grilli and Murtinu 2015). Similarly, we find a limited treatment effect of GVC on the performance of the entrepreneurial companies that have also received PVC financing. Fourth, the literature has also recognized that the effect of GVC on the performance of the companies in their portfolios seems to be more positive when GVC investors syndicate with PVC investors (Grilli and Murtinu 2014; Bertoni and Tykvovà 2015; Brander et al. 2015). Although we do not focus specifically on syndication, we provide positive evidence of the ability of GVC to attract PVC investors to the deal and, therefore, to facilitate syndication. Fifth, we support the idea that GVC increases their portfolio companies' chances of being financed by PVC; thus, we also contribute to the more compelling policy debate regarding the effect of GVC on the development of national VC industries (e.g., Cumming 2013). Many papers support the hypothesis that direct public investments in the VC market crowds out PVC investments (e.g., Armour and Cumming 2006). However, other studies find that direct public investment has a positive impact on the aggregate pool of PVC investments and actually helps leverage the market (e.g., del-Palacio et al. 2012). Our evidence is consistent with public investment's positive impact and suggests that at least part of these aggregate trends can be explained at the micro level by the certification effect of GVC.

The implications of our analysis are important for policy makers who are interested in designing effective GVC initiatives. Our work supports the importance of government interventions in the form of direct investments in high-tech entrepreneurial companies through funds that are owned and managed by governmental bodies. We find that the bulk of the value that GVC adds is the result of GVC firms' screening abilities. This finding can have important implications for the design of GVC funds, which should attempt to certify high-potential companies, not enhance companies' value without PVC. The managers of these funds must continue to invest in their screening skills to maintain and improve GVC firms' reputations as screening agents for PVC firms. Our work also has implications for practitioners in the VC industry and entrepreneurs. Our results indicate that PVC investors can use the fact that an entrepreneurial company has received GVC as a screening criterion to select good investment opportunities. Moreover, entrepreneurs should consider GVC a valuable source of finance that can improve the entrepreneurial company's chances of raising additional funding from private investors.

Our study has some limitations that are linked to the relatively limited size and the high-tech nature of the dataset; however, these limitations open interesting avenues for future research. First, a promising area of investigation would be to understand the conditions where GVC certification is stronger. In sectors that are characterized by higher information asymmetries it is more likely that PVC investors find GVC certification valuable. Although the present paper focused on high-tech sectors, which are typically characterized by higher information asymmetries, it would also be interesting to test the effectiveness of GVC certification in low-tech sectors. Second, recent works suggest that interaction effects among different types of VC investors may have different outcomes (see, e.g., Cumming and Johan 2009; 2010). In fact, we find that the effect of GVC certification particularly concerns independent and corporate VC investors, not bank-affiliated VC investors. However, future research may go one step further and evaluate, for example, whether and how the composition of the VC syndicates that are generated by GVC certification affects the performance of entrepreneurial companies. Third, it would also be interesting to test whether GVC investors can

attenuate the “herding behavior” of PVC investors by provoking changes in their investment patterns. Fourth, future research should consider the heterogeneous nature of GVC programs – such as their experience, internal organization and objectives – for example, by using fine-grained data obtained through surveys. These characteristics may influence the screening and certification capabilities of GVC investors. Lastly, a more comprehensive analysis should also consider the relation between social gain and public expenses that is linked to this type of government intervention.

References

Alperovych Y, Hübner G, Lobet F (2015) How does governmental versus private venture capital backing affect a firm's efficiency? Evidence from Belgium. J Bus Ventur 30:508–525. doi: 10.1016/j.jbusvent.2014.11.001

Armour J, Cumming DJ (2006) The legislative road to Silicon Valley. Oxf Econ Pap 58:596–635. doi: 10.1093/oep/gpl007

Audretsch DB (1995) Innovation, growth and survival. Int J Ind Organ 13:441–457. doi: 10.1016/0167-7187(95)00499-8

Audretsch DB, Bönte W, Mahagaonkar P (2012) Financial signaling by innovative nascent ventures: The relevance of patents and prototypes. Res Policy. doi: 10.1016/j.respol.2012.02.003

Audretsch DB, Thurik R (2001) Linking entrepreneurship to growth. OECD Sci Technol Ind Work Pap. doi: 10.1787/736170038056

Balakrishnan N, Rao CR (2004) Handbook of Statistics, Volume 23: Advances in Survival Analysis. Elsevier

Baum JAC, Silverman BS (2004) Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. J Bus Ventur 19:411–436. doi: 10.1016/S0883-9026(03)00038-7

Becker GS (1983) A Theory of Competition Among Pressure Groups for Political Influence. Q J Econ 98:371. doi: 10.2307/1886017

Belsley DA, Kuh E, Welsch RE (1980) Regression diagnostics: identifying influential data and sources of collinearity. John Wilet & Sons, Ltd, Hoboken, New Jersey

Berger AN, Udell GF (1990) Collateral, loan quality and bank risk. J Monet Econ 25:21–42. doi: 10.1016/0304-3932(90)90042-3

Bertoni F, Groh AP (2014) Cross-Border Investments and Venture Capital Exits in Europe. Corp Gov An Int Rev 22:84–99. doi: 10.1111/corg.12056

Bertoni F, Martì Pellon J (2011) Financing Entrepreneurial Ventures in Europe: The Vico Dataset.

Bertoni F, Tykvovà T (2015) Does governmental venture capital spur invention and innovation? Evidence from young European biotech companies. Res Policy 44:925–935. doi: doi:10.1016/j.respol.2015.02.002

Brander J a., Du Q, Hellmann TF (2015) The Effects of Government-Sponsored Venture Capital: International Evidence. Rev Financ 19:571–618. doi: 10.1093/rof/rfu009

Brander JA, Amit R, Antweiler W (2002) Venture-Capital Syndication: Improved Venture Selection vs. The Value-Added Hypothesis. J Econ Manag Strateg 11:423–452. doi: 10.1111/j.1430-9134.2002.00423.x

Brander JA, Egan EJ, Hellmann TF (2008) Government sponsored versus private venture capital: Canadian evidence. University of Chicago Press, Cambridge

Burchardt J, Hommel U, Kamuriwo DS, Billitteri C (2014) Venture capital contracting in theory and practice: Implications for entrepreneurship research. Entrep Theory Pract. doi: 10.1111/etap.12104

Buzzacchi L, Scellato G, Ughetto E (2013) The investment strategies of publicly sponsored venture capital funds. J Bank Financ 37:707–716. doi: 10.1016/j.jbankfin.2012.10.018

Carpenter RE, Petersen BC (2002a) Is the Growth of Small Firms Constrained by Internal Finance? Rev Econ Stat 84:298–309. doi: 10.1162/003465302317411541

Carpenter RE, Petersen BC (2002b) Capital Market Imperfections, High-Tech Investment, and New Equity Financing. Econ J 112:F54–F72. doi: 10.1111/1468-0297.00683

Chan Y-S (1983) On the positive role of financial intermediation in allocation of venture capital in a market with imperfect information. J Finance 38:1543–1568. doi: 10.2307/2327586

Chang SJ (2004) Venture capital financing, strategic alliances, and the initial public offerings of Internet startups. J Bus Ventur 19:721–741. doi: 10.1016/j.jbusvent.2003.03.002

Chemmanur TJ, Krishnan K, Nandy D (2011) How does Venture Capital Financing Improve Efficiency in Private Firms? A Look Beneath the Surface. Rev Financ Stud. doi: 10.2139/ssrn.1025322

Colombo MG, Bertoni F, Quas A (2015) Pattern of venture capital investment in Europe. Small Bus Econ 45:543–560. doi: 10.1007/s11187-015-9662-0

Colombo MG, Cumming DJ, Vismara S (2014) Governmental venture capital for innovative young firms. J Technol Transf 1–15. doi: 10.1007/s10961-014-9380-9

Colombo MG, Giannangeli S, Grilli L (2012) Public subsidies and the employment growth of high-tech start-ups: assessing the impact of selective and automatic support schemes. Ind Corp Chang 22:1273–1314. doi: 10.1093/icc/dts037

Cox D (1972) Regression models and life-tables. J R Stat Soc 34:187–220.

Croce A, Martì Pellon J, Murtinu S (2013) The impact of venture capital on the productivity growth of European entrepreneurial firms: “Screening” or “value added” effect? J Bus Ventur 28:489–510. doi: 10.1016/j.jbusvent.2012.06.001

Cumming DJ (2013) Public economics gone wild: Lessons from venture capital. Int Rev Financ Anal. doi: 10.1016/j.irfa.2013.10.005

Cumming DJ (2007) Government policy towards entrepreneurial finance: Innovation investment funds. J Bus Ventur 22:193–235. doi: 10.1016/j.jbusvent.2005.12.002

Cumming DJ, Grilli L, Murtinu S (2014) Governmental and independent venture capital investments in Europe: a firm-level performance analysis. J Corp Financ 1–28. doi: 10.1016/j.jcorpfin.2014.10.016

Cumming DJ, Johan S (2014) Venture's economic impact in Australia. J Technol Transf. doi: 10.2139/ssrn.2194450

Cumming DJ, Johan S (2008) Preplanned exit strategies in venture capital. Eur Econ Rev 52:1209–1241. doi: 10.1016/j.euroecorev.2008.01.001

Cumming DJ, Johan S (2009) Venture Capital and Private Equity Contracting: An International Perspective. ELSEVIER SCIENCE BV

Cumming DJ, Johan S (2010) Venture Capital Investment Duration. J Small Bus Manag 48:228–257. doi: 10.1111/j.1540-627X.2010.00293.x

Cumming DJ, Macintosh JG (2006) Crowding out private equity: Canadian evidence. J Bus Ventur 21:569–609. doi: 10.1016/j.jbusvent.2005.06.002

Da Rin M, Hellmann TF, Puri M (2011) A survey of venture capital research.pdf. NBER Work Pap No. 17532:1–134.

Da Rin M, Nicodano G, Sembenelli A (2006) Public policy and the creation of active venture capital markets. J Public Econ 90:1699–1723. doi: 10.1016/j.jpubeco.2005.09.013

del-Palacio I, Zhang XT, Sole F (2012) The capital gap for small technology companies: public venture capital to the rescue? Small Bus Econ 38:283–301. doi: 10.1007/s11187-010-9275-6

Denis DJ (2004) Entrepreneurial finance: an overview of the issues and evidence. J Corp Financ 10:301 – 326. doi: 10.1016/S0929-1199(03)00059-2

Devenow A, Welch I (1996) Rational herding in financial economics. Eur Econ Rev 40:603–615. doi: 10.1016/0014-2921(95)00073-9

Dushnitsky G, Lenox MJ (2005) When do incumbents learn from entrepreneurial ventures? Corporate venture capital and investing firm innovation rates. Res Policy 34:615–639. doi: 10.1016/j.respol.2005.01.017

Eckhardt JT, Delmar F, Shane S (2006) Multistage Selection and the Financing of New Ventures. Manage Sci 52:220–232. doi: 10.1287/mnsc.1050.0478

Engel D, Keilbach M (2007) Firm-level implications of early stage venture capital investment — An empirical investigation. J Empir Financ 14:150–167. doi: 10.1016/j.jempfin.2006.03.004

European Commission (1998) Fostering Entrepreneurship in Europe: priorities for the future. Brussels

Fang L (2005) Investment bank reputation and the price and quality of underwriting services. J Finance 60:2729–2761. doi: 10.1111/j.1540-6261.2005.00815.x

Feldman MP, Kelley MR (2006) The ex ante assessment of knowledge spillovers: Government R&D policy, economic incentives and private firm behavior. Res Policy 35:1509–1521. doi: 10.1016/j.respol.2006.09.019

Ferrary M (2010) Syndication of Venture Capital Investment: The Art of Resource Pooling. Entrep Theory Pract 34:885–907. doi: 10.1111/j.1540-6520.2009.00356.x

Freedman DA, Sekhon JS (2010) Endogeneity in Probit Response Models. Polit Anal 18:138–150. doi: 10.1093/pan/mpp037

Gans JS, Stern S (2003) When Does Funding Research By Smaller Firms Bear Fruit?: Evidence From The Sbir Program. Econ Innov New Technol 12:361–384. doi: 10.3386/w7877

Gilson RJ (2003) Engineering a Venture Capital Market: Lessons from the American Experience. Stanford Law Rev 55:1067–1103. doi: 10.2139/ssrn.353380

Giot P, Schwienbacher A (2007) IPOs, trade sales and liquidations: Modelling venture capital exits using survival analysis. J Bank Financ 31:679–702. doi: 10.1016/j.jbankfin.2006.06.010

Gompers PA (1995) Optimal Investment, Monitoring, and the Staging of Venture Capital. J Finance 50:1461–1489. doi: 10.1111/j.1540-6261.1995.tb05185.x

Gompers PA (1996) Grandstanding in the venture capital industry. J financ econ 42:133–156. doi: 10.1016/0304-405X(96)00874-4

Gompers PA, Kovner A, Lerner J (2009) Specialization and Success: Evidence from Venture Capital. J Econ Manag Strateg 18:817–844. doi: 10.1111/j.1530-9134.2009.00230.x

Gompers PA, Lerner J (2001) The Venture Capital Revolution. J Econ Perspect 15:145–168. doi: 10.1257/jep.15.2.145

Gompers PA, Levin DZ (1999) What drives venture capital fundraising? Brookings Pap Econ Act Microeconomics. doi: 10.2139/ssrn.57935

Gorman M, Sahlman WA (1989) What do venture capitalists do? J Bus Ventur 4:231–248. doi: 10.1016/0883-9026(89)90014-1

Griliches Z (1992) The Search for R&D Spillovers. Scand J Econ 94:29–47. doi: 10.3386/w3768

Grilli L, Murtinu S (2014) Government, venture capital and the growth of European high-tech entrepreneurial firms. Res Policy 43:1523–1543. doi: 10.1016/j.respol.2014.04.002

Grilli L, Murtinu S (2015) New technology-based firms in Europe: market penetration, public venture capital, and timing of investment. Ind Corp Chang 24:1109–1148. doi: 10.1093/icc/dtu025

Hall BH (2002) The Financing of Research and Development. Oxford Rev Econ Policy 18:35–51. doi: 10.1093/oxrep/18.1.35

Hall J, Hofer CW (1993) Venture capitalists' decision criteria in new venture evaluation. J Bus Ventur 8:25–42. doi: 10.1016/0883-9026(93)90009-T

Harrison RT, Mason CM (1992) International perspectives on the supply of informal venture capital. J Bus Ventur 7:459–475. doi: 10.1016/0883-9026(92)90020-R

Heckman JJ (1979) Sample Selection Bias as a Specification Error. Econometrica 47:153–161.

Hochberg Y V, Ljungqvist A, Lu Y (2007) Whom you know matters: Venture capital networks and investment performance. J Finance 62:251–301. doi: 10.1111/j.1540-6261.2007.01207.x

Hoenen S, Kolympiris C, Schoenmakers W, Kalaitzandonakes N (2014) The diminishing signaling value of patents between early rounds of venture capital financing. Res Policy. doi: 10.1016/j.respol.2014.01.006

Jääskeläinen M, Maula MVJ, Murray GC (2007) Profit distribution and compensation structures in publicly and privately funded hybrid venture capital funds. Res Policy 36:913–929. doi: 10.1016/j.respol.2007.02.021

Jeng LA, Wells PC (2000) The determinants of venture capital funding: evidence across countries. J Corp Financ 6:241–289. doi: 10.1016/S0929-1199(00)00003-1

Kaplan SNN, Strömberg P, Stromberg P (2001) Venture Capitalists As Principals: Contracting, Screening, and Monitoring. Am Econ Rev 91:426–430. doi: 10.3386/w8202

Katila R, Rosenberger JD, Eisenhardt KM (2008) Swimming with Sharks: Technology Ventures, Defense Mechanisms and Corporate Relationships. Adm Sci Q 53:295–332. doi: 10.2189/asqu.53.2.295

Kelly R (2011) The Performance and Prospects of European Venture Capital. EIF Work Pap 2011/09 1–24.

Keuschnigg C, Nielsen SB (2001) Public Policy for Venture Capital. Int Tax Public Financ 8:557–572. doi: 10.1023/A:1011251920041

Keuschnigg C, Nielsen SB (2004) Start-ups, venture capitalists, and the capital gains tax. J Public Econ 88:1011–1042. doi: 10.1016/S0047-2727(03)00046-X

Lach S (2002) Do R&D subsidies stimulate or displace private R&D? Evidence from Israel. J Ind Econ 50:369–390. doi: 10.1111/1467-6451.00182

Leleux B, Surlemont B (2003) Public versus private venture capital: seeding or crowding out? A pan-European analysis. J Bus Ventur 18:81–104. doi: 10.1016/S0883-9026(01)00078-7

Lerner J (2009) Boulevard of broken dreams: why public efforts to boost entrepreneurship and venture capital have failed--and what to do about it. Princeton University Press

Lerner J (2002) When Bureaucrats Meet Entrepreneurs: The Design of Effective "Public Venture Capital" Programmes. Econ J 112:F73–F84. doi: 10.1111/1468-0297.00684

Lerner J (1999) The Government as Venture Capitalist: The Long-Run Impact of the SBIR Program. J Bus 72:285–318. doi: 10.3905/jpe.2000.319960

Lerner J (1994a) Venture capitalists and the decision to go public. J financ econ 35:293–316. doi: 10.1016/0304-405X(94)90035-3

Lerner J (1994b) The Syndication of Venture Capital Investments. Financ Manag 23:16–27.

Lockett A, Murray GC, Wright M (2002) Do UK venture capitalists still have a bias against investment in new technology firms. Res Policy 31:1009–1030. doi: 10.1016/S0048-7333(01)00174-3

Luukkonen T, Deschryvere M, Bertoni F (2013) The value added by government venture capital funds compared with independent venture capital funds. Technovation 33:154–162. doi: 10.1016/j.technovation.2012.11.007

Luukkonen T, Deschryvere M, Bertoni F, Nikulainen T (2011) Importance of the non-financial value added of government and independent venture capitalists. ETLA Discuss Pap No. 1257:1–29.

Maddala GS (1983) Limited Dependent and Qualitative Variables in Econometrics. Cambridge University Press, Cambridge, UK

Manigart S, Baeyens K, Van Hyfte W (2002) The survival of venture capital backed companies. Ventur Cap An Int J Entrep Financ 4:103–124. doi: 10.1080/13691060110103233

Manigart S, Lockett A, Meuleman M, et al. (2006) Venture Capitalists' Decision to Syndicate. Entrep Theory Pract 30:131–153. doi: 10.1111/j.1540-6520.2006.00115.x

Megginson WL, Weiss KA (1991) Venture Capitalist Certification in Initial Public Offerings. J Finance 46:879–903. doi: 10.1111/j.1540-6261.1991.tb03770.xfr

Meuleman M, De Maeseneire W (2012) Do R&D subsidies affect SMEs' access to external financing? Res Policy 41:580–591. doi: 10.1016/j.respol.2012.01.001

Murray GC, Lott J (1995) Have UK venture capitalists a bias against investment in new technology-based firms? Res Policy 24:283–299. doi: 10.1016/0048-7333(93)00767-N

Peltzman S (1976) Toward a more general theory of regulation. J Law Econ 19:211–240. doi: 10.3386/w0133

Revest V, Sapio A (2012) Financing technology-based small firms in Europe: what do we know? Small Bus Econ 39:179–205. doi: 10.1007/s11187-010-9291-6

Rosenbaum PR, Rubin DB (1985) Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. Am Stat 39:33–38.

Sahlman WA (1990) The structure and governance of venture-capital organizations. J financ econ 27:473–521. doi: 10.1016/0304-405X(90)90065-8

Smith JA, Todd PE (2005) Does matching overcome LaLonde's critique of nonexperimental estimators? J Econom 125:305–353. doi: 10.1016/j.jeconom.2004.04.011

Stam E, Garnsey EW (2008) Enterpreneurship in the knowledge economy. In: Publishing EE (ed) Creat. wealth from Knowl. Meet. Innov. Chall. p 405

Sunley P, Klagge B, Berndt C, Martin R (2005) Venture capital programmes in the UK and Germany: In what sense regional policies? Reg Stud 39:255–273. doi: 10.1080/0034340052000321913

Takalo T, Tanayama T (2010) Adverse selection and financing of innovation: Is there a need for R&D subsidies? J Technol Transf 35:16–41. doi: 10.1007/s10961-009-9112-8

Tian X (2011) The causes and consequences of venture capital stage financing. J financ econ 101:132–159. doi: 10.1016/j.jfineco.2011.02.011

Ueda M (2004) Banks versus Venture Capital: Project Evaluation, Screening, and Expropriation. J Finance 59:601–621. doi: 10.1111/j.1540-6261.2004.00643.x

Tables

Table 1: Distribution of GVC-backed and control group entrepreneurial companies by industry, country and founding period

	GVC-backed companies		Control group companies	
	No	%	No	%
Industry				
Internet	14	7.65	953	11.77
TLC	8	4.37	376	4.65
Software	67	36.61	3,660	45.22
ICT manufacturing	31	16.94	1,457	18.00
Biotech and pharmaceuticals	48	26.23	793	9.80
Other high-tech industries	15	8.20	855	10.56
Total	*183*	*100.00*	*8,094*	*100.00*
Country				
Belgium	25	13.66	873	10.79
Finland	28	15.30	728	8.99
France	34	18.58	1,678	20.73
Germany	31	16.94	1,303	16.10
Italy	13	7.10	1,030	12.73
Spain	34	18.58	833	10.29
United Kingdom	18	9.84	1,649	20.37
Total	*183*	*100.00*	*8,094*	100.00
Founding period				
Founded before 1999	94	51.37	4,321	53.39
Founded in 1999 or 2000	52	28.42	1,723	21.29
Founded after 2000	37	20.22	2,050	25.33
Total	*183*	*100.00*	*8,094*	*100.00*

Table 2: Distribution of entrepreneurial companies, according to the year of receipt of a first round of GVC and PVC.

Year	First round of GVC		First round of PVC	
	No	%	No	%
1994	6	3.28	4	0.71
1995	10	5.46	7	1.24
1996	12	6.56	17	3.01
1997	18	9.84	37	6.55
1998	15	8.20	36	6.37
1999	12	6.56	65	11.50
2000	31	16.94	148	26.19
2001	27	14.75	94	16.64
2002	14	7.65	52	9.20
2003	20	10.93	46	8.14
2004	18	9.84	56	9.91
2005-2007	0	0	3	0.54
Total	*183*	100.00	*565*	100.00

Table 3: Distribution of GVC-backed and control group entrepreneurial companies according to the receipt of a first round of PVC, receipt of a second round of PVC and successful exit

	GVC-backed companies		Control group companies	
	No	%	No	%
Panel A. All entrepreneurial companies				
Received a first round of PVC	94	51.37	471	5.82
Did not receive a first round of PVC	89	48.63	7,623	94.18
Total	*183*	*100.00*	*8,094*	*100.00*
Panel B. Entrepreneurial companies that received a first round of PVC				
Received a second round of PVC	36	38.30	161	34.18
Did not receive a second round of PVC	58	61.70	310	65.82
Total	*94*	*100.00*	*471*	*100.00*
Listed or acquired	33	35.11	119	25.27
Still independent and private or liquidated	61	64.89	352	74.73
Total	*94*	*100.00*	*471*	*100.00*
Panel C. Entrepreneurial companies that did not receive a first round of PVC				
Listed or acquired	13	14.61	391	5.13
Still independent and private or liquidated	76	85.39	7,232	94.87
Total	*89*	*100.00*	*7,623*	*100.00*

Table 4: Descriptive statistics on the time between a company's founding year, the first round of GVC, the first round of PVC, the second round of PVC and successful exit for GVC-backed and control group companies

Variable	GVC backed companies			Control group companies		
	No	Mean	Std. Dev.	No	Mean	Std. Dev.
Company age at the time of the first round of GVC	183	2.33	2.86			
Time between first round of GVC and first round of PVC	94	0.86	1.82			
Company age at the time of the first round of PVC	94	3.20	3.04	471	2.27	2.67
Time between first PVC round and second round of PVC	36	2.11	1.04	161	2.22	1.40
Time between first PVC round and successful exit	33	5.48	2.68	119	5.08	2.76

Table 5: Summary statistics and correlation matrix

	Variable	N. of companies	N. of observ.	Mean	p50	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1	$PVC_{i,t}$	8,277	101,064	0.05	0.00	0.21	0.00	1.00	1.00											
2	$PVCsecond_{i,t}$	8,277	101,064	0.01	0.00	0.11	0.00	1.00	1.00[a]	1.00										
3	$SuccessfulExit_{i,t}$	8,277	101,064	0.00	0.00	0.04	0.00	1.00	0.70[a]	0.56[a]	1.00									
4	$PVCfundraising_{t-2}$	8,277	101,064	6.35	4.50	6.56	0.26	27.10	0.31[b]	0.04[b]	0.05[b]	1.00								
5	$GVCfundraising_{c,t-2}$	8,277	101,064	14.08	0.00	80.16	0.00	645.60	0.09[b]	0.05[b]	-0.05[b]	-0.04[c]	1.00							
6	$NumberIPO_{t-1}$	8,277	101,064	4.25	4.22	1.06	1.61	6.32	0.01[b]	-0.00[b]	0.08[b]	0.36[c]	0.00[c]	1.00						
7	$Age_{i,t}$	8,277	101,064	7.57	7.00	5.54	0.00	26.00	-0.09[b]	-0.02[b]	0.00[b]	0.04[c]	0.01[c]	-0.14[c]	1.00					
8	$TotalAssets_{i,t-1}$	8,277	101,064	6.00	5.88	1.77	0.00	15.69	0.17[b]	0.24[b]	0.23[b]	0.01[c]	-0.01[c]	-0.02[c]	0.25[c]	1.00				
9	$Patents_{i,t-1}$	8,277	101,064	0.05	0.00	1.16	0.00	119.97	0.01[b]	0.02[b]	0.01[b]	0.00[c]	-0.01[c]	0.00[c]	0.03[c]	0.09[c]	1.00			
10	$GVC_{i,t-1}$	8,277	101,064	0.02	0.00	0.12	0.00	1.00	0.61[a]	0.51[a]	0.48[a]	-0.02[b]	0.04[b]	-0.15[b]	0.01[b]	0.16[b]	0.01[b]	1.00		
11	$GVCamount_{i,t-1}$	8,277	101,064	0.02	0.00	0.21	0.00	8.79	0.24[b]	0.17[b]	0.10[b]	0.00[c]	0.00[c]	-0.01[c]	0.00[c]	0.05[c]	0.01[c]	0.65[b]	1.00	
12	$PVCamount_{i,t-1}$	8,277	101,064	0.23	0.00	3.29	0.00	282.12	0.32[b]	0.36[b]	0.12[b]	0.01[b]	0.01[c]	-0.01[c]	0.00[c]	0.05[c]	0.03[c]	0.12[b]	0.20[c]	1.00
13	$PVCexperience_{i,t-1}$	8,277	101,064	0.41	0.00	3.22	0.00	59.00	0.62[b]	0.20[b]	0.12[b]	0.02[b]	-0.03[c]	0.03[c]	-0.01[c]	0.06[c]	0.01[c]	0.14[b]	0.17[c]	0.21[c]

Legend: [a] Tetrachoric correlation, [b] Biserial correlation, [c] Pearson correlation.

Table 6: Balancing of the matching procedure

Variables	Mean in the year of the matching		T-test statistic
	GVC-backed companies	Matched companies	
$Age_{i,t}$	2.305	2.301	0.010
$TotalAssets_{i,t-1}$	5.794	5.796	-0.010
$Patents_{i,t-1}$	0.012	0.015	-0.170
$GVCfundraising_{c,t-2}$	2.888	2.808	0.060

Table 7: Likelihood of GVC-backed companies and their matched peers of receiving a first round of PVC

The table reports the estimated coefficients and, in brackets, the robust standard error of the coefficients of the Cox event-history type models. The dependent variable is $PVC_{i,t}$ and time defined by $Age_{i,t}$. We use Efron's (1977) correction for ties, and * p < 0.10; ** p< 0.05; *** p< 0.01. Industry, country and period dummies are used to stratify the hazard function. The last row of the table indicates that the proportional hazard assumption holds (test based on the analysis of Schoenfeld residuals). The multicollinearity of the variables was tested by using a variance inflation factor (VIF) analysis. In all estimates, the average VIF is below the 5 threshold (Belsley et al. 1980).

	I		II		III		IV	
$TotalAssets_{i,t-1}$	0.265	***	0.237	**	0.239	**	0.235	**
	(0.096)		(0.098)		(0.096)		(0.099)	
$Patents_{i,t-1}$	0.296	***	0.292	***	0.330	***	0.296	***
	(0.075)		(0.052)		(0.080)		(0.054)	
$NumberIPO_{t-1}$	0.031	*	0.033	*	0.033	*	0.033	*
	(0.018)		(0.017)		(0.018)		(0.018)	
$PVCfundraising_{t-2}$	0.702	***	0.741	***	0.735	***	0.744	***
	(0.175)		(0.169)		(0.175)		(0.170)	
$GVC_{i,t-1}$			1.314	***			1.213	***
			(0.250)				(0.341)	
$GVCamount_{i,t-1}$					0.965	**	0.148	
					(0.409)		(0.375)	
N. of observations	9,819		9,819		9,819		9,819	
N. of companies	971		971		971		971	
N. of failures	116		116		116		116	
Risk	9,757		9,757		9,757		9,757	
χ^2	51.14 (5)	***	97.93 (6)	***	54.58 (6)	***	97.54 (7)	***
Pseudo R^2	0.087		0.116		0.103		0.116	
Pseudo lnL	-269.64		-261.25		-265.07		-261.183	
χ^2 PH Assumption	7.99 (5)		11.24 (6)		12.54 (6)		11.39 (7)	

Table 8: Likelihood of receiving a first round of PVC – Robustness checks

The table reports the estimated coefficients and, in brackets, the robust standard error of the coefficients of the Cox event-history type models. The dependent variable is $PVC_{i,t}$ and time is defined by $Age_{i,t}$. We used the Efron (1977) correction for ties, and * p < 0.10; ** p< 0.05; *** p< 0.01. Country and period dummies are used to stratify the hazard function. Industry dummies are included in columns IV and V and to stratify the hazard function in all other columns. The last row of the table indicates that the proportional hazard assumption holds (test based on the analysis of Schoenfeld residuals).

	I Matching 1:7	II Matching 1:3	III Matching 1:5 using a pure propensity score	IV Random selection of a 1:5 control group	V Excluding co-investments	VI Excluding co-investments and companies not seeking PVC
$TotalAssets_{i,t-1}$	0.178**	0.129	0.149*	0.252***	0.208 **	0.573 ***
	(0.084)	(0.080)	(0.087)	(0.076)	(0.103)	(0.210)
$Patents_{i,t-1}$	0.191***	0.254***	-0.012	-0.254	0.372 ***	0.584
	(0.051)	(0.041)	(0.425)	(0.185)	(0.063)	(0.814)
$PVCfundraising_{t-2}$	0.035**	0.029*	0.038**	0.035**	0.036	-0.019
	(0.016)	(0.016)	(0.016)	(0.014)	(0.029)	(0.046)
$numberIPO_{c,t}$	0.652***	0.647***	0.531***	0.672***	0.953 ***	0.881 ***
	(0.153)	(0.156)	(0.156)	(0.139)	(0.233)	(0.303)
$GVC_{i,t-1}$	1.304***	0.840**	1.197***	0.968***	2.552 ***	1.861 **
	(0.325)	(0.332)	(0.385)	(0.371)	(0.399)	(0.879)
$GVCamount_{i,t-1}$	0.000	0.060	0.074	0.265	-0.073	-0.017
	(0.305)	(0.294)	(0.405)	(0.370)	(0.338)	(0.337)
N. of observations	12,679	6,567	9,608	11,668	9,619	1,416
N. of companies	1,251	677	951	1,095	900	140
N. of failures	132	112	120	139	45	25
Risk	12,617	6,505	9,546.9	11,596.1	9,574.1	1,372
χ^2	84.16 (7)***	1621.87 (12)***	61.51 (7)***	69.11 (7)***	1038.33 (12) ***	1125.58 (12) ***
Pseudo R^2	0.095	0.086	0.086	0.095	0.283	0.246
Pseudo lnL	-337.17	-348.53	-281.02	-297.91	-125.067	-38.639
χ^2 PH Assumption	6.75 (7)	7.55 (12)	7.79 (7)	10.48 (7)	11.49 (12)	6.71 (12)

Table 9: Likelihood of PVC-backed companies of receiving a second round of PVC or of being listed or acquired.

The table reports the estimated coefficients and, in brackets, the robust standard error of the coefficients of the Cox event-history type models. Thedependent variables are indicated in the first row of the table and the time is defined by the number of years since the first PVC round. We use Efron's (1977) correction for ties, and * p < 0.10; ** p< 0.05; *** p< 0.01. Industry, country and period dummies are used to stratify the hazard function. The last row of the table indicates that the proportional hazard assumption holds (test based on the analysis of Schoenfeld residuals). The multicollinearity of variables was tested using a variance inflation factor (VIF) analysis. In all estimates, the average VIF is below the 5 threshold (Belsley et al. 1980).

Dependent variable	$PVCsecond_{i,t}$		$SuccessfulExit_{i,t}$	
	I		II	
$TotalAssets_{i,t-1}$	0.019		0.222	
	(0.227)		(0.167)	
$Patents_{i,t-1}$	-0.082		0.124	**
	(0.215)		(0.055)	
$NumberIPO_{t-1}$	0.041		0.424	*
	(0.286)		(0.239)	
$PVCamount_{i,t-1}$	0.058	*	0.001	
	(0.030)		(0.005)	
$PVCexperience_i$	0.065	***	0.012	
	(0.017)		(0.012)	
$GVC_{i,t-1}$	1.427	*	-0.527	
	(0.764)		(0.576)	
$GVCamount_{i,t-1}$	-0.220		0.153	*
	(0.187)		(0.090)	
N. of observations	668		850	
N. of companies	116		116	
N. of failures	43		40	
Risk	552		734	
χ^2	42.68 (7)	***	24.91 (7)	***
Pseudo R^2	0.18		0.107	
Pseudo lnL	-46.805		-51.209	
χ^2 PH Assumption	6.49 (7)		3.76 (7)	

Table 10: Switching regression with endogenous switching for GVC-backed and control group companies

The table reports the estimated coefficients and, in brackets, the robust standard error of the coefficients of a set of Probit models whose dependent variables are shown in the first row of the table, and * p < 0.10; ** p< 0.05; *** p< 0.01. Industry, country and period dummies are included. The constant term is omitted from the table.

	GVC selection	*$PVC_{i,t}$*		*$PVCsecond_{i,t}$*		*$SuccessfulExit_{i,t}$*	
	I	II	III	IV	V	VI	VII
Sample	All companies	GVC-backed	Control group	GVC-backed	Control Group	GVC-backed	Control Group
$Age_{i,t}$	-0.099 ***	0.013	-0.095 ***	-0.278 ***	-0.092 ***	0.077 **	0.011
	(0.014)	(0.124)	(0.008)	(0.107)	(0.017)	(0.036)	(0.015)
$TotalAssets_{i,t-1}$	0.014	0.287 ***	0.079 ***	0.218 **	0.063 **	0.038	0.176 ***
	(0.023)	(0.108)	(0.012)	(0.096)	(0.031)	(0.083)	(0.032)
$Patents_{i,t-1}$	-0.012	0.044	0.013	-0.042	0.055	0.308 **	0.061 **
	(0.062)	(0.301)	(0.009)	(0.256)	(0.051)	(0.132)	(0.031)
$GVCfundraising_{c,t-1}$	0.001 **						
	0.00						
$PVCfundraising_{t-2}$	0.007	-0.026	0.013 ***				
	(0.005)	(0.020)	(0.003)				
$NumberIPO_{t-1}$	0.157 ***	0.188	0.242 ***	0.168	0.077	-0.012	0.077
	(0.037)	(0.246)	(0.027)	(0.176)	(0.047)	(0.083)	(0.055)
IMR		-0.680	6.455 **	2.349 **	-6.044	-0.120	-51.067 ***
		(1.277)	(2.677)	(1.007)	(5.936)	(0.095)	(15.845)
$GVCamount_{i,t-1}$		-0.102		-0.041		0.105 **	
		(0.163)		(0.092)		(0.051)	
$PVCamount_{i,t-1}$				0.026 **	0.036 ***	0.003	0.004
				(0.012)	(0.009)	(0.002)	(0.004)
$PVCexperience_i$				0.021 **	0.001	0.009	0.002
				(0.010)	(0.004)	(0.007)	(0.003)
N. of observations	101,000	864	97,374	530	3,018	687	3,737
N. of companies	8,277	112	8,094	94	471	94	471
χ^2	4414.3 (22) ***	1130.5 (23) ***	4382.4 (18) ***	1857.1 (20) ***	161.31 (22) ***	42.13 (20) ***	801.2 (21) ***
Pseudo R^2	0.163	0.242	0.187	0.249	0.178	0.124	0.093
Pseudo lnL	-731.83	-80.426	-2424	-98.834	-500.1	-115.99	-459.42

Table 11: "What if" analysis associated with an endogenous switching regression model

This table reports the actual and hypothetical probabilities of receiving a first round of PVC, a second round of PVC and a successful exit for GVC-backed and control group companies. * p < 0.10; ** p< 0.05; *** p< 0.01, for a t-test of the mean difference. Standard errors are in parentheses.

Panel A: Receiving a first round of PVC	Mean	t-test p-value
GVC-backed companies at least one year after investment		
Estimated probability of a first round of PVC if they were not GVC-backed	0.005	
Actually received a first round of PVC	0.027	
Difference	-0.021	***
	(0.005)	
Control group companies		
Estimated probability of a first round of PVC if they were GVC-backed	0.053	
Actually received a first round of PVC	0.005	
Difference	0.048	***
	(0.000)	
Panel B: Receiving a second round of PVC , only PVC-backed companies	Mean	t-test p-value
GVC-backed companies		
Estimated probability of a second round of PVC if they were not GVC-backed	0.068	
Actually received a second round of PVC	0.069	
Difference	-0.001	
	(0.011)	
Control group companies		
Estimated probability of a second round of PVC if they were GVC-backed	0.045	
Actually received a second round of PVC	0.051	
Difference	-0.009	
	(0.004)	
Panel C: Having a successful exit, only PVC-backed companies	Mean	t-test p-value
GVC-backed companies		
Estimated probability of having a successful exit if they were not GVC-backed	0.039	
Actually had a successful exit	0.048	
Difference	-0.010	
	(0.008)	
Control group companies		
Estimated probability of having a successful exit if they were GVC-backed	0.035	
Actually had a successful exit	0.030	
Difference	0.005	*
	(0.003)	