Governmental and independent venture capital investments in Europe: a firm-level performance analysis

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Abstract

This paper examines the impact of government versus private independent venture capital (VC) backing on the exit performance of entrepreneurial firms. Our analyses are based on the VICO dataset, which avoids the coding problems of VC type in the Thompson Financial SDC dataset. The data indicate that private independent VC-backed companies have better exit performance than government-backed companies. Mixed-syndicates of private-independent and governmental VC investors give rise to a higher (but not statistically different) likelihood of positive exits than that of IVC-backing. Our findings are not influenced by the composition of the syndicate in terms of size and institutional heterogeneity. Our results remain stable after controlling for endogeneity concerns, selection bias, omitted variables bias, legal and institutional differences across countries and over time through several econometric techniques. Moreover, our results are not driven by: i) the holding period of the different types of VC investors; ii) the potential signaling effect of GVC towards IVC investors; iii) the firm's financial structure and net cash-flow ratio; iv) the investment stage; v) the distance between the VC investor and the target company.

Keywords: independent venture capital; governmental venture capital; syndication; exit performance; public-private partnership

1. Introduction

Venture Capital ("VC") is one of the most tailored financing modes for young high-tech companies (Gompers and Lerner, 2001; Yung, 2009; Vismara et al., 2012). First, venture capitalists ("VCs") provide the financial resources young high-tech companies lack due to capital market imperfections (Andrieu and Groh, 2012).[1] Second, VCs

[1] Capital market imperfections are due to some peculiar characteristics of young high-tech companies, such as: i) the technology-intensive nature of their business model; ii) their lack of reputation; iii) and the intangible nature of their assets, which cannot be used as collateral when bargaining with banks and other

perform coaching (Sahlman, 1990; Groh et al., 2010) and monitoring activities (Gompers, 1995; Lerner, 1995; Kanniainen and Keuschnigg, 2003, 2004; Wang and Zhou, 2004; Giot and Schwienbacher, 2007; Hege et al., 2009; Cressy et al., 2007; Dihiya and Ray, 2012). Third, VCs provide access to business contacts and alliance partners (Riyanto and Schwienbacher, 2006; Huang et al., 2008; Wang and Wang, 2012a,b).

VC firms are funds in which a management company raises capital from a pool of limited partners (e.g. university endowments, banks, pension funds, insurance companies, wealthy individuals, family offices, asset managers), selects target companies and tries to achieve a profitable exit, usually through an IPO or a trade-sale (Sahlman, 1990; Gompers and Lerner, 2001; Nahata, 2008; Nahata et al., 2014).

However, due to historical reasons and to the distinctive features of legal and institutional environments, the supply of VC is extremely different across countries (Groh et al., 2010; Cumming and Johan, 2013). In particular, the gap suffered from European Union (EU) Member States in comparison to the United States (US) is not negligible, both in terms of fundraising and investments. According to an official report of the European Parliament (2012), in 2010 US funds' fundraising activity reached € 10.1 billion (0.09% of GDP) compared to only € 3.3 billion in Europe (0.03% of GDP). In terms of investments, the VC amount in the US reached a value of € 11.8 billion (0.11% of GDP) compared to € 3.5 billion (0.03% of GDP) in Europe. The recent financial crisis has further "stretched the scissors" (Kraemer-Eis and Lang, 2011).

The scant development of the European VC market has in the recent past resulted in a series of policy initiatives at the EU level (the most important one is probably the Risk Capital Action Plan in 1998; European Commission, 1998) directed towards various playing-level fields (e.g., measures aimed at increasing stock market openness and/or labor market flexibility, tax incentives) in order to stimulate both the supply and the demand side of the VC market.

These efforts also led to the emergence of a peculiar feature in the EU context: a higher presence of governmental VC (GVC, henceforth) funds than in the US (Leleux and Surlemont, 2003), i.e. VC funds set-up and managed by a company entirely

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traditional financial institutions (Berger and Udell, 1998; Carpenter and Petersen, 2002; Denis, 2004; Bertoni et al., 2013).

possessed by governmental (or public administration) bodies.[2] The economic rationale behind the setting up of GVC funds (GVCs, henceforth) is to adopt a "*hands-on policy approach*" in the VC market and (try to) alleviate the typical chicken-egg paradox of markets where the deal flow is scarce because of shortage of VC but the supply of VC is thin due to the low number of promising business targets.[3]

Despite the high number of GVCs in Europe (e.g., Biotech Fonds Vlaanderen in Belgium, SITRA in Finland, CDC Innovation in France, TBG in Germany, Piemontech in Italy, Axis Participaciones Empresariales in Spain, Scottish Enterprise in the UK), the extant literature on the impact of GVC on portfolio companies' performance in Europe is very limited. And to the best of our knowledge, there has not been any attempt in the corporate finance literature to compare their performance with the one achieved by the typical 'Silicon Valley style' independent venture capital (IVC) funds operating in the same European context.

As a matter of fact, many previous works dealing with the issue have used a macro perspective to explain which country-specific policy (Groh et al., 2010; Cumming and Johan, 2013) and institutional factors might foster the VC industry in Europe (Cumming and Johan, 2013). Other works examined the performance of extra-European GVC programs.[4] Finally, very few country-specific studies focused on the impact of GVC on portfolio companies' growth performance (e.g., Beuselinck and Manigart, 2000 in Belgium, or Balboa et al., 2007 in Spain). There are a few exceptions in recent working papers, but the trouble is that such papers are based on the Thompson Financial SDC dataset which may misreport fund types (for example, in Canada and Australia, over 50% of the transactions are reported as being from the wrong fund type). Grilli and Murtinu (2014a,b) analyze the impact of GVC on the growth performance (in terms of sales and

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[2] The extant literature lacks a commonly accepted definition of GVC. Examples of definitions are: i) equity (or equity-like) investments in young firms, or policy measures aimed at favoring other financial intermediaries to engage in such investments (Gompers and Lerner, 2004); ii) programs that help high-tech industries through direct VC initiatives and tax policies (Cumming and Johan, 2013); iii) hybrid public/private funds (Jääskeläinen et al. 2007). In this work, we adopt the criterion followed by the Thomson One database that classifies the VC funds according to the governance of the fund.

[3] Independent venture capital (IVC) investments in Europe as a share of GDP are only 25% of the US ones (Kelly, 2011).

[4] Some examples are OnPoint Technology and In-Q-Tel programs in the US (Mara, 2011), the Yozma program in Israel (Avnimelech and Teubal, 2006) and the IIF in Australia (Cumming and Johan, 2013).

employees) of young high-tech companies located in 7 European countries (Belgium, Finland, France, Germany, Italy, Spain and the United Kingdom). Using the VICO database, through several econometric techniques, they showed that GVC-backed companies would have followed similar growth patterns even without any GVC investment. Overall, they show that independent (and other typologies of private) VC funds are more effective than GVCs in spurring the growth of portfolio companies. The only positive impact exerted by governmental funds is found to be confined to the syndication with independent (and other private) VC operators, and this result holds only if specific conditions are met.[5]

As to this latter aspect, another untapped gap in the extant literature is the lack of empirical evaluation about the performance, from the investor's point of view, of mixed syndicates composed by GVC and IVC funds (IVCs, henceforth) in the European VC market. This reflects a more general dearth of studies on syndication activities between different types of VC investors *in any geographical* context. But the issue is relevant. As claimed by Gompers and Lerner (2004), VC investors often tend to syndicate their investments rather than going alone.

Syndication is reputed to be beneficial for several reasons. First, it may improve the screening process through (at least) a 'second opinion' (Gompers and Lerner, 2004; Casamatta and Haritchabalet, 2007). Second, it may increase capital infusion into the portfolio company and leverage the coaching potential of investors through the exploitation of complementary financial and non-financial resources, skills, networks and industry expertise of syndicate members (Andrieu and Groh, 2012). Third, it leads to a reduction of the overall portfolio risk (Gompers and Lerner, 2004) and may convey a signal towards capital markets about the quality of the focal VC-backed company, which may ultimately have a positive influence on the likelihood of a successful exit (Cumming and Johan, 2013).

In principle, these benefits (especially the second one of the above-exposed list) could be particularly pronounced when different types of VC investors join the syndicate (Bertoni et al., 2013). However, the intrinsic differences between IVC and GVC investors

[5] For example, Grilli and Murtinu (2014b) found that the impact of public-private syndication on the sales growth of high-tech companies is positive and statistically significant (ranging from +62.90% to +63.54%) but only if the syndicate targets very young companies.

might also entail agency and transaction costs (e.g., Wright and Lockett, 2003; Cumming et al., 2007). These costs should be higher when the objectives of syndicate partners are incompatible, as might be the case of IVC and GVC investors. As highlighted by Chahine et al. (2012: p. 180), syndicate members 'have different objectives which can result in principal-principal conflicts of interests among members of a VC syndicate'.

Our contribution aims at filling these gaps. Our research questions may be summarized as follows: i) are GVCs by their own able to lead to a positive exit in comparison with traditional IVC investors?; ii) how do syndicated investments by GVC and IVC funds perform?; and iii) do different structures of mixed IVC-GVC syndicates play a differential effect on the exit performance?

We answer to these research questions through the VICO database, a novel firm-level longitudinal dataset sponsored by the European Union under the 7° Framework Program (for more details, see Section 3). The VICO dataset includes 8,370 companies from seven European countries (Belgium, Finland, France, Germany, Italy, Spain and the UK) out of which 759 received VC funding between 1994 (or subsequent firm's foundation year) and 2004. In the sample used in this work, firms are observed from 1991 (or year of a firm's foundation) to 2010 (or year of a firm's exit from the dataset).

As is customary in the finance literature dealing with VC and exit (e.g., Gompers and Lerner, 2004; Wang and Wang, 2010, 2012b, Cumming and Johan, 2013), our analysis hinges on a multinomial logit approach, distinguishing between positive outcomes (IPOs or trade-sales) and negative ones (liquidations). Our empirical findings highlight a positive contribution of IVC-backing on the likelihood to reach a positive exit. However, the impact of GVC is negligible. More interestingly, mixed IVC-GVC syndicated investments lead to a higher (but not statistically different) likelihood of a positive exit than that of IVC-backing. This positive impact of IVC-GVC syndicates is not found to be influenced by the composition of the syndicate in terms of size and institutional heterogeneity. These results remain stable after controlling for endogeneity concerns, selection bias and omitted variables bias through several econometric techniques: multinomial probit models, semi-parametric Cox-type survival models, panel multinomial logit with random effects, panel probit models on matched samples, and Instrumental Variables (IV) linear probability models. We also controlled for legal and institutional differences across countries and over time, including accounting conservatism, accounting disclosure, debt enforcement, regulation of entry, procedural formalism of dispute resolution and property protection rights, creditor rights, stock market capitalization, and the European Union convergence. Moreover, our results are not driven by alternative explanations, such as: i) the holding period of the different types of VC investors; ii) the potential signaling effect of GVC towards IVC investors; iii) the firm's financial structure and net cash-flow ratio; iv) the investment stage; and v) the distance between the VC investor and the target company.

The paper is organized as follows. Section 2 discusses issues associated with stand-alone GVC investments versus syndicated GVC-IVC investments. Section 3 describes the data. Section 4 explains the methodology. Section 5 presents the results and robustness tests. Section 6 tests whether our results are driven by alternative explanations. Section 7 concludes.

2. Governmental VC Funds and Government-Private Partnerships

In this section we consider three related issues. First, why might GVCs have differential exit performance results relative to IVCs? Second, why might the syndication of GVCs and IVCs impact exit performance? Third, why might the structure in terms of the size and institutional heterogeneity of the syndicate on which GVCs and IVCs operate influence exited performance?

The venture capital literature has identified three primary reasons why GVCs may perform worse than IVCs. First, GVCs are created by statute or some other political and regulatory process, and not through private negotiations among contracting parties. In the case of limited partnership venture capital funds, for example, institutional investors (as the limited partners) and the fund manager (as the general partner) contract with each other to efficiently set the terms upon which the funds will be invested into entrepreneurial firms. These covenants include terms such as restrictions on the size of investments, use of debt, co-investment, public disclosure of fund matters, and no-fault divorce provisions, among other things. These clauses mitigate agency problems in fund management, and hence facilitate maximization of returns and investee performance. The frequency of use of these clauses appropriately and efficiently depends on economic, human capital, and institutional conditions (see Gompers and Lerner, 2004 for US evidence, and Cumming and Johan, 2006, 2013 for international evidence). By contrast, GVC covenants are determined by regulators, typically have no resemblance to the covenants used by IVCs, do not vary over time and across fund managers, and are hence much less efficient than IVC covenants (Cumming and MacIntosh, 2007). Second, GVCs are believed to have less efficient compensation terms relative to IVCs. IVCs typically are structured with a 2% fixed fee (based on committed capital) and a 20% performance fee, with hurdle rates and clawbacks in the event of poor performance. These fee terms are contractually negotiated and vary depending on economic conditions and the characteristics and experience of the fund managers (see Gompers and Lerner, 2004, for US evidence, and Cumming and Johan, 2013, for international evidence). GVCs, by contrast, are reputed[6] to have compensation terms that are comparatively invariant across managers and funds, and invariant over time. As such, agency problems in effort are exacerbated among GVCs, and GVCs face employee retention problems among better fund managers that show promise and generate outside offers. Third, GVCs have a lack of independence in decision making. IVCs, by contrast, are legally independent by virtue of the limited partnership structure – limited partners do not get involved in the day-to-day operation of the fund, otherwise they risk losing their limited liability status. GVCs are much different, and have been known to face pressure to invest in marginal quality projects, as well as geographically remote projects. Relatedly, while IVCs regularly replace founding entrepreneurs as the CEO and have contractual rights to do so (Cumming, 2008; Cumming and Johan, 2013), GVCs face political pressure to not fire founding entrepreneurs and risk political problems if they do so. Furthermore, GVCs face pressure to pursue non-financial related goals, such as employment maximization (Cumming and MacIntosh, 2007).

There are a number of reasons why GVC-IVC syndicated relations may enhance performance and overcome the issues identified immediately above. Following the ordering of the three problems with GVCs identified above, the first issue involves limited partnership covenants. By syndicating with IVCs, the investee firms financed by GVCs still enjoy the structural advantages of IVC limited partnerships, which are not

[6] Unfortunately there does not exist data or empirical studies on this point. Further research is warranted.

compromised by sole financing with a less efficient GVC structure. Second, investee firms are likewise not compromised by sole financing from GVCs with less efficient compensation terms, and enjoy the benefits associated with IVC compensation terms. To the extent that GVC and IVC efforts are substitutable for growing the entrepreneurial firm, the disadvantages of inefficient GVC compensation can be significantly mitigated. Third, decision making is independent among IVCs (i.e., not subject to influence from institutional investors), and not subject to political pressure. This independence mitigates the agency problems of inefficient decision making associated with political pressure from government bodies affecting GVC investment decisions. Finally, an advantage of the GVC-IVC partnership is that the independent sources of networks and contacts that can help the entrepreneurial firms grow are more expansive than merely an IVC syndicate. GVCs would be expected to have access to governmental contacts that may beneficial to the entrepreneurial firm, which could include government-related suppliers and customers, and enable streamlined and faster regulatory approval of business matters that are in the entrepreneurial firm's interest. GVCs enhance IVC value added by expanding the scope of networks and enabling connections to government-related suppliers and customers that could expand the investee firm's set of opportunities to maximize growth. In short, because political connections are valuable, and because IVCs can mitigate the cost of inefficient GVC structures, IVC-GVC syndicated partnership are expected to enable entrepreneurial firms perform better.

Finally, there are a number of reasons why the structure of the syndicate in terms of its size and institutional heterogeneity on which GVCs and IVCs operate might influence exited performance. On the negative side there are two factors to consider. First, larger funds may give rise to diseconomies of scale and limited attention problems where fund managers sit on too many boards of directors, not maximizing their value-added provided to any single investee (Cumming and Dai, 2011). Second, there can be free-riding amongst syndicated VCs, whereby if the effort of one VC is substitutable with that of another then overall value-added is mitigated as VCs are in conflict with one another in terms of who is responsible for assisting the investee firm. Nevertheless, there are five factors to consider on the positive side (each of these positive outcomes is summarized in Gompers and Lerner, 2004). First, syndication improves decision making and thereby mitigates adverse selection problems, given different individuals with more diverse backgrounds (as would be expected among individuals among GVCs and IVCs) have different expertise to carry out more effective due diligence overall. Second, syndication facilitates improved value added where the effort of different VCs are complementary. Third, diverse syndicated VCs may collude to overstate the quality of the entrepreneurial firm and hence maximize exit opportunities in terms of who will buy the entrepreneurial firm and at what price. Fourth, diversity in syndication enables diversification and risk sharing, which in turn facilitates investment decisions that may not otherwise have been made, and hence improves the scope of feasible outcomes. Finally, diversity in syndicates mitigates hold-up and renegotiation problems vis-à-vis the entrepreneurial firm in each staged investment round, and hence improves incentives for the entrepreneur to maximize firm value and exit possibilities.

In sum, prior literature is consistent with the view that GVCs investing by themselves are expected to have worse exit performance, GVCs syndicated with IVCs are expected to perform better, and that the size and structure of the syndicate can affect agency problems amongst VCs and between VCs and entrepreneurs that can in turn affect exit performance. Below, we test these propositions by examining for the first time the relation between syndicate structure and exit performance.

3. Data

3.1. Data Collection Procedure

In this work, we use the VICO database. The VICO database represents the final output of a research project funded by the 7th Framework Programme of the European Commission. The VICO database includes data on young high-tech VC-backed and non-VC-backed (but potentially targetable by VC investors) companies that: i) are located in seven European countries (Belgium, Finland, France, Germany, Italy, Spain and the United Kingdom); ii) are less than 20 years old in 2010; iii) were borne as independent firms (i.e., not controlled by other business organizations); and iv) operate in high-tech (manufacturing and services) industries (see Table 1). The VICO database includes surviving and non-surviving companies (i.e., companies that ceased operations or were acquired), whether they are VC-backed companies or not.

Overall, the VICO database consists of 8,370 firms, 759 of which are VC-backed (for a full description of the database, see Bertoni and Martí, 2011). In this work, the observed time-span is 1991-2010.

As regards the identification of VC-backed companies, several proprietary and commercial sources were used. Country-specific proprietary sources are the yearbooks of the Belgium Venture Capital and Finnish Venture Capital Associations, the ZEW Foundation Panel (Germany), the RITA directory and Private Equity Monitor (Italy), the José Martí Pellón Database (Spain), and the Library House (now Venture Source, UK). Commercial sources are the Thomson One database, VCPro-Database, and Zephyr. Moreover, whenever possible, the data were cross-checked with those available from public sources (e.g., websites and annual reports of VC investors, press releases and press clippings, and initial public offering prospectuses).

This data collection process allows us to ensure that the VICO database offers an extensive representation of the European population of VC-backed companies (for more details, see European Parliament, 2012). Even though the most popular database in the VC literature is the Thomson One database, this latter is known to under-represent investments made by non independent VCs (Ivanov and Xie, 2010: p. 135), especially in Europe. As common in the VC literature, the VICO dataset includes seed, early-stage, late-stage and expansion capital investments; while, LBOs, real estate, distressed debt funds and other private equity investments are not included.

Due to the necessity of a minimum number of post-investment observations to evaluate the impact of VC on the performance of portfolio companies, the VICO database includes VC-backed companies which obtained their first round of VC funding between 1994 and 2004 and were less than 10 years old at that time.

For the identification of non-VC-backed companies, we used the Amadeus database. All available vintage years of Amadeus were used to build the population such that non-surviving companies are included. Analogously to VC-backed companies, specific country-specific proprietary sources were used in order to improve the coverage of the dataset (e.g., Creditreform in Germany, the database of the Union of Italian Chambers of Commerce in Italy).

A complete description and documentation of the procedures and sources used in the data gathering process and on all of the portfolio company-, investment-, and investor-level variables included in the VICO dataset, is provided in Bertoni and Martì (2011).

3.2. Descriptive Statistics

To classify companies backed by different types of VC investors, we focus on the year of the first VC investment. We removed from the dataset companies that received a first investment by corporate, bank-affiliated and university-sponsored VC investors; or by VC investors that have missing name, address and/or contact information in the VICO database. It is worth noting that we removed such companies if and only if corporate, bank-affiliated and university-sponsored VC investors did not syndicate with IVCs or GVCs at the time of the first VC investment. We used this criterion to let the counterfactual of companies not backed by IVCs, GVCs or mixed IVC-GVC syndicates as clean as possible. Thus, among VC-backed companies, we keep companies that received a first investment by IVCs, GVCs or a mixed IVC-GVC syndicate. According to these three "states of nature", we classify companies as IVC-backed, GVC-backed or SYND-backed, respectively.[7]

The breakdown by country and industry of IVC-backed, GVC-backed, and SYND-backed companies is provided in Table 1.

The representation of IVC-backed companies reflects the development of financial markets across countries, being larger in the UK (128 IVC-backed companies, 30.48% of the total IVC-backed companies), followed by Germany (19.76%) and France (13.81%). The situation is different by looking at the representation of GVC-backed companies, where Spain has the greatest share (24.41%), followed by Germany (16.54%) and Finland (16.54%). France has the greatest share of SYND-backed companies (35.48%) followed by Germany (17.74%) and Belgium (14.52%). Software represents the main target industry both for IVCs (39.76%) and for GVCs (32.28%). Biotechnology & Pharmaceutical represents the second target market both for IVCs (18.33% in conjunction with ICT manufacturing) and GVCs (27.56%). SYND-backed companies show the same industrial representation of GVC-backed companies: the first industry is software (50%)

[7] Our definition of syndication closely adheres to the definition provided by Gompers and Lerner (2004). Given that our analysis is not at round-level, we implicitly assume that IVCs and GVCs syndicate when they invest in the same portfolio company in the same year.

followed by Biotechnology and Pharmaceutical (24.19%) and ICT manufacturing (16.13%).

[Table 1 about here]

Table 2 illustrates the distribution of positive (IPOs and trade-sales) and negative (liquidations) exits according to the type of VC investor at the time of the first VC investment. The highest percentage of publicly- or privately-traded VC-backed companies received a first investment by an IVC investor (74.77%), followed by a mixed IVC-GVC syndicate (14.02%) and a GVC investor (11.21%). In terms of liquidated VC-backed companies, the highest percentage of them was initially invested by an IVC investor (69.61%). GVC-backed companies represent more than one fifth of liquidated VC-backed companies (21.57%). While, SYND-backed companies represent less than one tenth of liquidated VC-backed companies (8.82%).

[Table 2 about here]

4. Empirical Framework

We compare the effects of IVC-, GVC- and SYND-backing on the probability of a successful/unsuccessful exit using a multinomial logit model. The use of multinomial logit models is the most common choice in the literature about the impact of VC on exit (e.g., Cumming et al., 2006; Cumming, 2008; Cumming and Johan, 2013). We estimate the following multinomial logit model:[8]

$$\textit{Exit Type} = f(\textit{VC backing, VC size, VC diversity, Controls}). \qquad (1)$$

[8] In order to take into account the panel nature of the VICO database, standard errors are clustered at portfolio company-level.

Exit Type is a categorical variable and assumes three different values: 1 for positive outcomes (IPOs or trade-sales),[9] 2 for liquidations, and 0 for the baseline category (companies that did not go public, were not acquired and are still in operation). The likelihood to fall in the outcome j is $p_j = \exp(X'\beta_j)/[1 + \sum_{j=1}^{3} \exp(X'\beta_j)]$. *Exit type* is always equal to zero for all companies that did not go public, were not acquired and are still in operation. For companies that went public or have been acquired, it is zero in all years prior to the first positive event (IPO or trade-sale), and it equals one in the year of the first positive exit. It is set to missing in the following years. In the same way, for liquidated companies, *Exit type* is zero in all years prior to liquidation, and it equals two in the year of liquidation. It is set to missing in the following years.

VC backing includes 3 step dummy variables (*IVC*; *GVC*; *SYND*) which switch from 0 to 1 in the year following the first VC investment. Similarly to Chahine et al. (2012), we include *VC size* and *VC diversity*. *VC size* represents the yearly number of VC investors backing the young high-tech company at time t-1. *VC diversity* looks at the VC affiliation (i.e., independent, corporate, bank-affiliated, university-sponsored, governmental) and counts the number of sub-groupings of each VC type backing the young high-tech company at time t-1. *Controls* includes several classes of variables at portfolio company-level. First, we include a set of country dummies, (2-digit SIC) industry dummies, and year dummies. Second, we include the logarithm of firm age (measured by the years since firm foundation) and its squared term: *Age* and *Age*^{2}. Third, following Chahine et al. (2012), we include a bubble dummy (*Bubble*) which is equal to 1 whether the first VC investment was received in the years 1999 or 2000. Moreover, we take into account the time elapsed since the first VC receipt (proxied by the number of years since the first VC investment): *TimeFromVC*. Fourth, we introduce a measure of firm size (*Size*), proxied by the logarithm of headcount at time t-1. Fifth, we control for the operative performance through a measure of profit margin (measured by the ratio net income/sales) at time t-1 (Richard et al., 2009): *ProfitMargin*. Note that net income and sales value have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005). Finally,

[9] In the VC literature is quite common to pool together IPOs and trade-sales as positive exits. For instance, see e.g., Cumming and Dai (2013) and Gompers et al. (2009).

we control for the innovative performance through the inclusion of the logarithm of the patent stock at time t-1 (with yearly depreciation=0.15): *PatentStock*.

In Table 3, we report some descriptive statistics for IVC-backed, GVC-backed, SYND-backed and non-VC-backed companies. In terms of *VC Size*, SYND-backed companies show on average a higher yearly number of VC investors in their equity (3.3) than IVC-backed companies (2) and GVC-backed ones (1.4). As to *VC diversity*, not surprisingly, SYND-backed companies are on average financed by a higher number of types of VC investors. The average is slightly higher than 2, meaning that generally when governmental and independent VC operators syndicate is rare that other typologies of investor (corporate, bank-affiliated and university-sponsored) join the syndicate. For IVC-backed companies and GVC-backed ones the mean value of the variable is 1.4 and 1.2, respectively. Age distributions are similar across all companies (around 7 years old). IVCs are more likely to invest during the bubble period than GVCs: more than (almost) 40% of IVC (SYND)-backed companies received their first VC investment in the period 1999-2000. SYND-backed companies are bigger than other companies: on average, SYND-backed companies reach a size of about 39 employees, while headcount is 36 for IVC-backed, 26 for GVC-backed, and 24 for non VC-backed companies. On average, non VC-backed companies show a higher operating performance than VC-backed companies (especially if compared to SYND-backed ones). Finally, SYND-backed companies are on average more innovative (1.9 patents) than GVC-backed companies (0.7 patents), IVC-backed companies (0.4 patents) and non VC-backed ones (0.2 patents).

[Table 3 around here]

5. Findings

5.1. Results

Results from the multinomial logit estimates are shown in Table 4. In columns I and III, we show the results related to the likelihood of a positive exit (IPO or trade-sale); while, in columns II and IV, we show the findings related to the likelihood of a negative exit (liquidation). In columns I and II, we show the estimates related to the baseline model. The aim is to estimate the (potentially) different impact of IVC-, GVC-, and

SYND-backing on exit, whatever the number/heterogeneity of the investors in the equity of the focal young high-tech company. In columns III and IV, we insert *VC Size* and *VC Diversity* to investigate: i) what is their role on exit performance; and ii) whether the baseline results of IVC-, GVC-, and SYND-backing are unchanged or not.

It is worth noting that we report the relative-risk ratios (instead of the estimated coefficients). This implies that a coefficient greater than 1 must be interpreted as a positive impact on the focal exit performance. In the same way, a coefficient smaller than 1 must be interpreted as a negative impact on the focal exit performance.[10]

In column I, our empirical findings highlight the superior ability of IVCs to reach a positive exit, if compared to GVCs. The impact of IVCs on the likelihood of an IPO or a trade-sale is positive and statistically significant at 1%. The coefficient of the impact of GVC is of lower magnitude and it is not statistically significant. SYND-backed companies have a higher likelihood to reach a positive exit than IVC-backed companies (and GVC-backed ones). However, the Wald test does not reject the null hypothesis of no difference between the coefficients of *IVC* and *SYND*. The impact of mixed IVC-GVC syndicates is positive and statistically significant at 1%. In column II, we see that VC-backing does not influence the likelihood of liquidation, whatever the type of VC-backing at the time of the first investment.

In column III, we turn to our augmented model that includes *VC Size* and *VC Diversity*. The positive impact of IVC-backing and SYND-backing on the likelihood of a positive exit is not found to be influenced by syndicate size (*VC size*) and institutional heterogeneity (*VC diversity*). The impact of IVC-backing is still positive and statistically significant at 1% (the magnitude is slightly lower than that in column I), and the economic significance is such that an IPO or a trade-sale is 87.3% more likely when an IVC investor is involved. The coefficient of the impact of GVC is still negligible and of lower magnitude than that of IVC-backing. Again, SYND-backed companies have a higher (but not statistically different) likelihood to reach a positive exit than IVC-backed

[10] Relative risk ratios offer an immediate interpretation of the magnitude of the effects. For example, a relative risk ratio of 2 means that on average a one unit increase in the given variable increases twice the probability of observing the outcome of interest with respect to the baseline category (when the other variables in the model are held constant) (Wooldridge, 2002). Note that in the main text we also report the marginal effects for the main variables of interest.

companies (and GVC-backed ones). The impact of mixed IVC-GVC syndicates is positive and statistically significant at 1%, and the marginal effect shows a 117.7% greater likelihood of a positive exit. The magnitude of the impact is slightly lower than that in column I. Also the results on liquidation (column IV) are fully in line with those of column II.

Results on *VC Size* and *VC Diversity* are interesting. While they have a negligible impact on the likelihood of a positive outcome (column III), their impact on liquidation is dramatic. The higher is the yearly number of VC investors in the equity of the focal young high-tech company, the lower appears the likelihood of a liquidation. This effect is statistically significant at 5%. The higher is the heterogeneity of the syndicate - in terms of different types of VC investors involved - the higher is the likelihood of a liquidation. This effect is statistically significant at 1% and its magnitude is extremely high (greater than 6).

[Table 4 around here]

As regards the control variables, we find a positive linear effect of firm age on the likelihood of a positive exit, while an inverted U-shaped effect on liquidation. Quite surprisingly, the coefficient of *Bubble* is always negligible: it seems that the time of the first VC investment does not exert any statistically significant influence on the exit outcome. The effect of *Size* is always statistically significant at 1%: bigger (smaller) firms are more likely to reach a positive (negative) exit. A higher level of *ProfitMargin* positively impacts (at 5%) the likelihood of a positive exit; while, its impact on the likelihood of liquidation is negligible. The higher is the time elapsed since the first VC investment, the higher is the likelihood of an IPO or a trade-sale. This effect is statistically significant at 5% in both columns I and III. This effect is also explored through the lens of a non-parametric hazard rate analysis performed in Figure 1. On the horizontal and vertical axes, there are the firm age and the estimated unconditional likelihood of a positive exit, respectively. The figure shows a quasi-monotonic increasing positive relationship between the time elapsed since the first VC investment and the likelihood of an IPO or a trade-sale until the firm age is ten years old. The hazard rate (the instantaneous probability of the positive outcome) maintains high between the age of ten and thirteen years old and then starts decreasing.[11] Finally, the impact of *PatentStock* on exit is positive. More specifically, there is a positive and statistically significant effect (at 5%) on the likelihood of a positive exit in column I. Instead, this effect is only close to significance (p-value = 0.102) even though is still positive in column III. Conversely, the effect of a firm's patent stock on the likelihood of a liquidation is negligible.

[Figure 1 around here]

[Figure 2 around here]

5.2. Selection Bias and Endogeneity Issues

Our results seem to show that private independent VCs (and mixed IVC-GVC syndicates) are better at developing their portfolio companies than governmental VCs. However, our multinomial logit approach might not take properly into account selection and endogeneity issues. Firstly, our results might be driven by a potential sample selection problem: private independent VCs (and mixed IVC-GVC syndicates) may be simply better at choosing and funding the most promising entrepreneurial firms. Secondly, in a competition to fund the best entrepreneurial firms, private independent VCs (and mixed IVC-GVC syndicates) may be more willing to offer the entrepreneur a better deal than GVCs do. Lastly, GVCs may systematically target portfolio companies which are overlooked by IVCs, and so the empirical comparison of IVC-backed and GVC-backed companies might be misleading (see also Section 6). It is worth noting that this latter problem should not be relevant in our context because of the presence of mixed IVC-GVC syndicates. Whatever the source of potential bias, the econometric problem is related to unobservable (or omitted) variables which explain both the likelihood to receive VC and the likelihood of exit (either positive or negative), and so a spurious correlation between the variables of interest (*IVC*, *GVC*, *SYND*, *VC size*, *VC diversity*)

[11] In Figure 2, we also perform the same non-parametric hazard rate analysis on the estimated unconditional likelihood of a negative exit. The figure shows a quasi-monotonic increasing positive relationship between the time elapsed since the first VC investment and the likelihood of a liquidation until the firm age is nine years old. Then, the hazard rate starts decreasing.

and exit might drive our results. To tackle these issues, we put in use five different identification strategies.

First, similarly to Chemmanur et al. (2011) and Croce et al. (2013), we inserted in our main specifications (Table 4, columns III and IV) three variables (*IVCpre*, *GVCpre*, *SYNDpre*), which are dummies that equal 1 in the years prior to the first VC investment - provided by an independent VC investor, a governmental VC fund or a mixed IVC-GVC syndicate, respectively - and 0 otherwise. The coefficients of such variables represent the screening activity performed by IVCs, GVCs and mixed IVC-GVC syndicates, respectively. We tried several (alternative) model specifications, with the three "VCpre" dummy variables that equal 1: i) from *t-2* to *t* - with *t* representing the year of the first VC investment - and 0 otherwise (Croce et al., 2013); ii) from *t-4* to *t* - with *t* representing the VC investment year - and 0 otherwise (Chemmanur et al., 2011); or iii) in all years prior to the first VC investment. Moreover, we also substituted each "VCpre" dummy variable with a series of impulse dummies from the year *t* to 5 years before the first VC funding (for a similar procedure, see Grilli and Murtinu, 2014a). Whichever the model specification, our main results are stable and are not influenced by the potentially different screening activity performed by IVCs, GVCs and mixed IVC-GVC syndicates (results are available upon request from the authors). The coefficients of the "VCpre" dummy variables are always smaller than one and statistically significant at 1%, whichever the type of the VC investor.[12] Thus, we found that VC-backed companies are less likely to have a positive or a negative exit than non-VC-backed companies in the years before VC funding. This (apparently counter-intuitive) finding is in line with the evidence based on the VICO dataset (e.g., Croce et al., 2013) and more generally confirms the findings of other EU-based studies (see Grilli, 2014 for a review), that

[12] We performed non-linear tests on the difference among the coefficients of *IVCpre*, *GVCpre*, and *SYNDpre*. The test statistics reported below refer to the model specification where the three "VCpre" dummy variables equal 1 in all years prior to the first VC investment. As regards the negative exits, such differences are never statistically significant: i) *IVCpre* - *GVCpre* = 0, P>|z|=0.515; ii) *IVCpre* - *SYNDpre* = 0, P>|z|=0.769; iii) *SYNDpre* - *GVCpre* = 0, P>|z|=0.976. As regards the positive exits, the tests on the differences are the following: i) *IVCpre* - *GVCpre* = 0, P>|z|=0.030; ii) *IVCpre* - *SYNDpre* = 0, P>|z|=0.615; iii) *SYNDpre* - *GVCpre* = 0, P>|z|=0.049. The most relevant issue is that the two statistically significant differences are negative, i.e. the IVC-backed and SYND-backed companies are less likely to have a positive exit than GVC-backed companies in the years before the first VC investment. So, the negligible impact of GVCs on the positive exit performance of their portfolio companies cannot be explained by the means of their supposed less effective screening activity than the one performed by IVCs and mixed IVC-GVC syndicates.

highlight a modest “pick-winner” function performed by the European VCs compared to the US counterparts. As explained by Croce et al. (2013, p. 503): 'This difference in screening abilities between US and European VCs might be explained by the higher level of development of US VC market (than that of the European VC market) in financing entrepreneurial firms'. In the same vein, Hege et al. (2003, p.4) claim that: 'venture capital firms in Europe [...] seem to be still lagging in their capacity to select projects. [...] US VCs have better screening skills (due to their greater experience) than European ones. It follows that US VCs are better at sorting out good projects from bad ones'.

Second, we tried to control for the quality of the entrepreneurial firm (especially in the pre-VC period for VC-backed companies). Following the most up-to-date corporate finance and entrepreneurial finance literatures, in our main specifications (Table 4, columns III and IV) we inserted: i) a variable (*PastSalesGrowth*) capturing the growth in sales value from the time t-2 to the time t-1 (see Chemmanur et al., 2010 for the use of past sales growth as a proxy of firm quality); and ii) the ratio between intangible assets and total assets (*ITA*) at time t-1 (according to Croce et al., 2013, this variable controls for the potentially different growth orientation between VC-backed and non-VC-backed companies before the first VC investment, and among the different types of VC-backing).[13] Results are shown in Table 5. We found a negligible impact of both variables on the likelihood of both positive and negative exits. This result seems to confirm the low screening ability of European VCs, whichever the type of VC backing.

[Table 5 around here]

Third, we estimated a multilevel latent variable model for unordered categorical responses, in which the latent variables are modeled as random effects.[14] We used the same model specification as shown in Eq. (1). The results are shown in Table 6 (columns I and II) and are in line with those exposed in Table 4 (columns III and IV). In column I,

[13] Sales value, total assets and intangible assets have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005).

[14] For computational problems, we cannot include in our model specification the industry dummies and country dummies. Instead, year dummies are not included because in this multilevel model each firm-year observation is a cluster.

the impact of IVC-backing is still positive and statistically significant (at 1%) on the likelihood of a positive exit, as well as the impact of SYND-backing (statistical significance at 5%). As in Table 4, the magnitude of SYND-backing is greater than that of IVC-backing, but the Wald test does not reject the null hypothesis of no difference between the two coefficients. The impact of GVC-backing is still negligible. Also in this case, syndicate size and institutional heterogeneity do not exert any impact on positive exit. As regards negative exits (column II), there is no impact of VC-backing *per se*. However, as in Table 4, there is a positive impact (statistically significant at 10%) of the institutional heterogeneity of the syndicate on liquidation. The only exception of these results when compared to those shown in Table 4 is the negligible impact of the yearly number of VC investors on the likelihood of a liquidation.

Fourth, for each of the three “states of nature” (IVC-backed, GVC-backed or SYND-backed companies), we performed a one-to-one propensity score matching without replacement in the year of the first VC investment to match each VC-backed company to a similar non-VC-backed twin firm (for applications of matching procedures in the VC literature, see e.g. Megginson and Weiss, 1991; Chemmanur et al., 2011; Puri and Zarutskie, 2012; Tian, 2012; Croce et al., 2013).[15] In estimating propensity scores, we resorted to a logit model with the same model specification used by Puri and Zarutskie (2012): firm age, firm size, country and industry dummies. The only obvious difference is that we use European countries (and not US regions) as geographic controls.[16] Then, we estimated two panel probit models in which the dependent variables are the likelihood of a positive exit and the likelihood of a negative exit, respectively. We used the same model specification as shown in Eq. (1). The results are shown in Table 6 (columns III and IV) and are in line with those exposed in Table 4 (columns III and IV). As regards the likelihood of a positive exit, the impact of IVC-backing is positive and statistically significant (at 1%). In the same way, SYND-backing has a positive and statistically significant (at 5%) effect. As in Table 4, the Wald test does not reject the null hypothesis

[15] We also performed the same matching procedure in the year before the first VC investment. Results are almost unchanged and are available upon request from the authors.

[16] Following the suggestions of Dehejia and Wahba (2002), we randomized our dataset before performing the matching procedure. We preferred a matching procedure without replacement due to the sufficient number of non VC-backed companies (Dehejia and Wahba, 2002), which can be used as potential matches of VC-backed companies.

of no difference between the two coefficients, even though the magnitude of SYND-backing is greater than that of IVC-backing. The impact of GVC-backing is still negligible. Also in this case, the size and the institutional heterogeneity of the syndicate do not exert any impact. As regards negative exits (column IV), there is no impact of IVC-backing and GVC-backing *per se*. However, there is a positive impact of SYND-backing on firm liquidation (significant at 5%). This represents the only exception when comparing these results with those shown in Table 4. As in Table 4, the likelihood of firm liquidation is impacted negatively by the yearly number of VC investors (statistical significance at 1%) and positively by the institutional heterogeneity of the syndicate (statistical significance at 5%).

[Table 6 around here]

Fifth, we resorted to an Instrumental Variables (IV) approach. More specifically, we estimated two pooled IV linear probability models (for a similar procedure, see Cornelli et al., 2013) with standard errors clustered at portfolio company-level in which the dependent variables are the likelihood of a positive exit and the likelihood of a negative exit, respectively.[17] We have two sets of covariates included in first-stage equations, where these equations capture the three possible VC-backing statuses of entrepreneurial firms (IVC-, GVC- and SYND-backing): i) a set of control variables which are also included in second-stage equations; and ii) a set of exclusion restrictions which are not included in second-stage equations. The control variables are: country dummies, industry dummies (2-digit SIC), year dummies, *Age*, *Age*^{2}, *Bubble*, *TimeFromVC*, *Size*, *ProfitMargin*, *PatentStock*. The exclusion restrictions are: an industry-level (3-digit SIC code) indicator on the importance of universities and higher education institutes as sources of external knowledge, calculated as the average value reported by the small firms (with less than 250 employees) that participated in the Innovation Benchmarking Survey jointly administered by the University of Cambridge and the Massachusetts

[17] The use of an IV probit model is prevented in our context given the discrete nature of our supposedly endogenous variables (*IVC*, *GVC*, *SYND*). The point is made clear by Wooldridge (2002, p. 472) who also suggests how linear probability models estimated through a two-stage least squares estimator represent in our case a reliable method (see also Angrist, 2001).

Institute of Technology in 2004 (*Science*); two industry-level (3-digit SIC code) indicators reflecting the effectiveness of formal (registration of design, trademarks, patents, confidentiality agreements, copyright) and informal (secrecy, complexity of design, lead-time advantage on competitors) mechanisms to protect innovation, calculated as the average values reported by the small firms (with less than 250 employees) that participated in the Innovation Benchmarking Survey jointly administered by the University of Cambridge and the Massachusetts Institute of Technology in 2004 (*Formal*, *Informal*); the ratio between government expenditures and GDP at country-level at time t-1 (*GovExp_GDP*: source: Eurostat); the IVC fundraising at country-level at time t-1 (*IVC_fundraising*: source: Thomson One), winsorized at the 1st and 99th percentiles; the overall equity capital invested at country-level at time t-1 (*Equity*: source: Thomson One), winsorized at the 1st and 99th percentiles; the GDP growth at country-level between time t and time t-1 (*GDP_Growth*; source: World Bank); the real GDP at country-level at time t-1 (*GDP*; source: World Bank), deflated by using the consumer price index (year 2005 is the reference year; source: Eurostat); and a dummy that equals 1 in the post-bubble period for ICT investments (*PostBubble_ICT*). It is worth noting that we employed this fifth identification strategy to estimate our baseline model (Table 4, columns I and II), because of the difficulty to find exclusion restrictions which acted as instruments for *VC size* and *VC diversity*. The results are shown in Table 6 (columns V and VI) and are in line with those exposed in Table 4. As regards the likelihood of a positive exit (column V), the impact of IVC-backing is positive and statistically significant (at 10%). In the same way, SYND-backing has a positive and statistically significant (at 10%) effect. As in Table 4, the Wald test does not reject the null hypothesis of no difference between the coefficients of SYND-backing and IVC-backing. GVC-backing does not exert a statistically significant impact. As regards negative exits (column VI), there is still no impact of VC-backing, whatever the type of VC-backing. In the last rows of Table 6 (columns V and VI), we reported the F statistics related to the first-stage regressions of the IV procedure. Whatever the dependent variable at the second-stage, in each first-stage regression the null hypothesis of weak instruments is rejected: the conventional threshold of 10 (Staiger and Stock, 1997) is always passed.

5.3. Legal and Institutional Issues

In our main estimations (Table 4, columns III and IV), we do not account for legal and institutional differences across countries and over time. However, the countries included in the VICO dataset are very different with respect to accounting conservatism, accounting disclosure, debt enforcement, regulation of entry, procedural formalism of dispute resolution and property protection rights, and creditor rights. In unreported regressions, we removed the country dummies from our main estimations and added the following country-level variables: i) an index of accounting conservatism, provided by Cumming and Walz (2010; *Country Earnings Aggressiveness Index* in their Table I); ii) a measure of accounting disclosure in private firms, provided by Cumming and Walz (2010; *Private Firm Accounting Indices* in their Table I); iii) an efficiency index of debt enforcement, provided by Djankov et al. (2008; *Efficiency* in their Table 2); iv) three indexes of regulation of entry, provided by Djankov et al. (2002; *Number of procedures*, *Time*, and *Cost* in their Table II): number of procedures, time and costs that start-ups must bear before starting their operations; v) an index of procedural formalism of dispute resolution, provided by Djankov et al. (2003; *Formalism index* in their Table IIb); and vi) an index aggregating creditor rights, provided by Djankov et al. (2007; *Creditor rights* in their Table 1). We also considered other indices from La Porta et al. (1998). Whichever the country-level variable employed, the results mirror those exposed in Table 4, in terms of both sign and magnitude. The impact of each country-level variable is fully in line with the evidence shown in the most relevant works in the literature on accounting, financial economics, economics, and political economy.

Furthermore, as shown in Table 1, the countries with the highest percentage of IVC-backed and GVC-backed companies are the UK and Spain, respectively. In 2010, the stock market capitalization/GDP ratio is about 85% in Spain, while it is 136% in the UK. Therefore, everything else being equal, an entrepreneurial firm should have a lower likelihood of becoming public in Spain than in the UK. Given that IPO is one of the two indicators of positive exit, we should check if a different degree of development of financial markets could be responsible for our findings. To test this, from our main estimations (Table 4, columns III and IV) we removed the country dummies and year dummies and added the country-level ratio between the stock market capitalization and the GDP at time t (source: World Bank; time period: 1991-2010). Also in this case, the results are fully in line with those shown in Table 4.

Lastly, during the time period of our study, the European countries included in the VICO dataset started with national laws that were quite different, but then such laws have been slowly converging because of the European Union convergence. Thus, from our main estimations (Table 4, columns III and IV) we removed the country dummies and year dummies and added an index of economic integration/convergence within the European Union at time t available for the countries included in the VICO dataset in the period 1999-2010, provided by König and Ohr (2013; *Overall integration* in their Table 2). Alternatively, from our main estimations (Table 4, columns III and IV) we substituted the country dummies and year dummies with their cross-products. As above, whichever the model specification employed, the results are almost the same as those shown in Table 4. All estimates are available upon request from the authors.

5.4. Robustness Checks

We performed several checks to test the robustness of our econometric results. Even though a multinomial logit approach is the most common choice in the literature on VC and exit (see Section 4), this methodology shows some weaknesses. First, multinomial logit models hinge on a strong assumption: the irrelevance of independent alternatives (IIA). To solve this problem, we estimated a multinomial probit regression with the same model specification as shown in Eq. (1). The results are shown in Table 7 (columns I and II). It is worth noting that we report the estimated coefficients (instead of the relative-risk ratios as in Table 4). In column I, as to the variables of interest (*IVC*, *GVC*, *SYND*, *VC size*, *VC diversity*), the results are fully in line with those exposed in Table 4. The impact of IVC-backing is still positive and statistically significant (at 1%) on the likelihood of a positive exit, as well as the impact of SYND-backing. This latter is statistically significant at 5% and its magnitude is higher than that of IVC-backing. As in our main results, the Wald test does not reject the null hypothesis of no difference between the two coefficients of *IVC* and *SYND*. The impact of GVC-backing on a positive exit is still negligible. These results on positive exit are not found to be influenced by syndicate size and institutional heterogeneity. As regards negative exits, in column II we see that VC-backing has no impact, whatever the type of VC-backing. However, as in Table 4: i) the higher is the yearly number of VC investors backing the focal portfolio company, the lower appears the likelihood of a liquidation (significant at 5%); ii) the higher is the institutional heterogeneity of the syndicate, the higher is the likelihood of a liquidation (significant at 1%).

[Table 7 around here]

Second, even though we clustered the standard errors at portfolio company-level, our pooled multinomial logit models might not take properly into account the panel nature of our dataset. So, we estimated two semi-parametric Cox-type survival models, in which the dependent variables are the hazard rate of a positive exit and the hazard rate of a negative exit, respectively. Firm age is the random variable to define the time of 'death' (i.e., first exit in a competing risk scenario). The choice to model non parametrically the hazard rates is due to their non-monotonic shape. As a matter of fact, the two hazard rates of positive and negative exits are increasing in the first years since firm foundation and then decreasing with firm age (see Figure 1 for positive exits and Figure 2 for negative exits).[18] The results are shown in Table 7 (columns III and IV) and are quite in line with those exposed in Table 4. As regards positive exits (column III), the impact of IVC-backing is positive and statistically significant (at 1%), as well as the impact of SYND-backing (significant at 5%). In this case, the magnitude of IVC-backing is slightly greater than that of SYND-backing. The impact of GVC-backing is still positive (as in Table 4) but weakly significant (at 10%). Also in this case, results on positive exit are not influenced by syndicate size and institutional heterogeneity. As regards negative exits (column IV), there is no impact of VC-backing *per se*. However, as in our main results, the yearly number of VC investors lowers the likelihood of a liquidation (statistical significance at 5%). And, the institutional heterogeneity of the syndicate positively impacts on the likelihood of a liquidation (statistical significance at 1%). Finally, we performed other four robustness tests/sensitivity analyses. First, we substituted the

[18] By construction, the logarithm of firm age and its squared term (*Age* and Age^2) cannot be included in the model specification.

variable *Bubble* with the variable *Bubble 1998-2000*. As shown in Table 8 (columns I and II), the results are almost unchanged. More interestingly, the impact of the time of the first VC investment is still negligible. Second, we tried alternative measures of operating performance. In Table 8, we substituted the variable *ProfitMargin* with: i) the ratio between the difference of sales value and payroll expenses and sales value (columns III and IV); ii) the ratio between EBITDA and total assets (columns V and VI); iii) the ratio between EBITDA and sales (columns VII and VIII); and iv) ROA - given by the ratio between net income and total assets - (columns IX and X). Also in this case, the results are almost unchanged. It is worth noting that sales value, payroll expenses, EBITDA, total assets and net income have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005). Third, in unreported regressions we inserted: i) a dummy variable that equals 1 whether the focal young high-tech company reports a loss (negative EBIT) in the year t-1 (Chahine et al., 2012); and ii) the ratio between current assets and total assets at time t-1 (Chahine et al., 2012). Results are almost unchanged and are available upon request from the authors. Note that EBIT, current assets and total assets have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005). Finally, according to Petersen (2009), we re-estimated the standard errors of the variables included in our models through a double-clustering by country and year. Results are almost unchanged and are available upon request from the authors.

[Table 8 around here]

6. Alternative Explanations

In this Section, we test whether our results (exposed in Table 4) can be driven by: i) the (potentially different) holding period of the different types of VC investors; ii) a potential signaling effect of GVC towards IVC investors; iii) the firm's financial structure and net cash-flow ratio; iv) the investment stage; and v) the distance between the VC investor and the target company.

6.1. Holding Period

VC investors provide value-adding services to their portfolio companies, and such services are more valuable when VC investors are actively involved in a firm's management. As claimed by Croce et al. (2013: p. 492): "During the holding period VCs provide help in defining strategic planning, assistance in management recruitment and compensation, access to their network of contacts (i.e. banks, suppliers and customers) and expertise in operational planning [...] all of which become valuable resources for the portfolio firm". Hence, if different types of VC investors are characterized by different holding periods, i.e. different types of VC investors systematically hold their equity stake for different time periods, our results might be driven by our (wrong) assumption to model *IVC*, *GVC* and *SYND* as 3 step dummy variables which switch "permanently" from 0 to 1 after the first VC investment. For instance, the estimated strong impact of mixed IVC-GVC syndicates might be related to the longer holding period of such mixed syndicated investments than that of IVC and GVC investments.

In order to control for this fact, we replaced the above-mentioned 3 step dummy variables (*IVC*, *GVC*, *SYND*) with 3 dummy variables: i) *IVC_holding* that equals one for the years after obtaining the first VC investment by an IVC investor until the end of the IVC investor's holding period, and zero otherwise; ii) *GVC_holding* that equals one for the years after obtaining the first VC investment by a GVC investor until the end of the GVC investor's holding period, and zero otherwise; and iii) *SYND_holding* that equals one for the years after obtaining the first VC investment by a mixed IVC-GVC syndicate until the end of the mixed IVC-GVC syndicate's holding period, and zero otherwise. The results are shown in Table 9 (columns I and II) and are in line with those exposed in Table 4. As regards the column I, the impact of IVC-backing is positive and statistically significant (at 5%) on the likelihood of a positive exit. In the same way, SYND-backing has a positive and statistically significant effect (at 1%). As in Table 4, the Wald test does not reject the null hypothesis of no difference between the coefficients of SYND-backing and IVC-backing, even though the magnitude of the former is greater than that of the latter. As in Table 4, the impact of GVC-backing, and the size and the institutional heterogeneity of the syndicate exert a negligible impact on the likelihood of a positive exit. As regards the column II, there is no impact of IVC-backing and GVC-backing, but there is a negative impact of SYND-backing on firm liquidation (significant at 1%). As in Table 4, the likelihood of firm liquidation is impacted negatively by the yearly number of

VC investors (statistical significance at 5%) and positively by the institutional heterogeneity of the syndicate (statistical significance at 1%).

6.2. Signaling

The negligible impact of GVC investors might be due to the fact that we did not model properly the dynamics and the interactions between GVC and IVC investors. Some portfolio companies might be characterized by very high spillovers or they could be too far from the product market. In both cases, IVCs could not be interested in targeting some companies. So, GVCs might exert a signaling function (Lerner, 2002) towards IVC investors that helps such (types of) portfolio companies access capital markets.

In order to take into account the sequence between GVC and IVC investments, we substituted the step variable GVC with two dummy variables: i) *IVC_post* that equals one from the year of a subsequent IVC investment, which occurs after the first GVC investment, and zero otherwise; and ii) *GVC_pre* that equals one for the years after obtaining the first VC investment by a GVC investor until the (potential) receipt of a subsequent IVC investment, and zero otherwise. The results are shown in Table 9 (columns III and IV) and are in line with those exposed in Table 4. As regards the positive exits (column III), the impact of IVC-backing is still positive and statistically significant (at 1%). Also SYND-backing exerts a positive and statistically significant (at 5%) effect, and its magnitude is greater than that associated with the coefficient of IVC-backing. Also in this case, when performing a Wald test, we cannot reject the null hypothesis of no difference between the coefficients of SYND-backing and IVC-backing. Even after splitting GVC-backing to control for (potential) subsequent IVC investments, the impact of GVC-backing is still negligible.[19] As in Table 4, the size and the composition of the syndicate exert a negligible impact on the likelihood of a positive exit. As regards the negative exits (column IV), there is no impact of VC-backing, whatever the type (and the potential sequence) of VC-backing. As in Table 4, the yearly number of VC investors exerts a negative impact on the likelihood of firm liquidation (statistical significance at 5%) and the institutional heterogeneity of the syndicate positively impacts the likelihood of a negative exit (statistical significance at 1%).

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[19] This result is in line with the findings of Grilli and Murtinu (2014a), which did not find a signaling effect exerted by GVCs towards IVCs in Europe in enhancing the growth of their portfolio companies.

6.3. Financial Structure and Cash-Flow Ratio

Now we consider the financial structure of portfolio companies. If different types of VC investors systematically choose companies which show different financial structures and/or net cash-flow ratios, i.e. GVC investors choose portfolio companies with more/less availability of capital and/or investment opportunities, our results exposed in Table 4 might be misleading. To some extent, we added to our model specification - eq. (1) - two additional variables: i) the ratio between short-term debt and total assets at time t-1 (*DTA*); ii) the ratio between net cash flow and total assets at time t-1 (*NCFTA*). When computing *DTA*, we used short-term debt because our sample is composed of young high-tech companies, and the majority of this debt is represented by bank loans. Companies with a low value of *DTA* may suffer from external capital constraints because of their high information asymmetries towards financial markets (Carpenter and Petersen, 2002), and thus some profitable investments cannot be pursued. As to *NCFTA*, it should capture the investment rate of young high-tech companies. In fact, the investment rate of this type of companies is strongly correlated with their net cash-flow (Bertoni et al., 2010). The results are shown in Table 10 (columns I and II) and are in line with those exposed in Table 4. In column I, we see that the impact of IVC-backing is positive and statistically significant (at 1%) on the likelihood of a positive exit. Also SYND-backing exerts a positive and statistically significant (very close to 5%) effect, and its magnitude is greater than that associated with the coefficient of IVC-backing. As in Table 4, we cannot reject the null hypothesis of no difference between the coefficients of SYND-backing and IVC-backing. The impact of GVC-backing is still negligible. As in Table 4, the size and the composition of the syndicate exert a negligible impact on the likelihood of a positive exit. Conversely, we find a positive and statistically significant effect (at 1%) of *DTA* on the likelihood of a positive exit. As regards the negative exits (column II), there is no impact of all types of VC-backing. As in Table 4, the yearly number of VC investors exerts a negative impact on the likelihood of firm liquidation (statistical significance at 5%) and the institutional heterogeneity of the syndicate positively impacts the likelihood of a negative exit (statistical significance at 1%). In this case, the impact of *DTA* is negligible. The impact of *NCFTA* is always negligible, whatever the exit type, even though the sign of the coefficient is the opposite: negative for positive exits and positive for firm liquidations.

6.4. Investment Stage

Our results in Table 4 might be driven by the stage of the investments engaged by different (types of) VC investors. If the different types of VC investors systematically choose companies in different stages of their life and there is a (positive or negative) correlation between the investment stage and the likelihood of a positive/negative exit, our main results could be biased. In order to control for this potential source of endogeneity (i.e., investment stage is an omitted variable), we inserted a dummy variable (*Earlystage*) that equals one for the companies which obtained the first VC investment in the first two years after firm foundation, and zero otherwise. This variable is set to zero for all non VC-backed companies. The results are shown in Table 10 (columns III and IV) and are in line with those exposed in Table 4. As regards the likelihood of a positive exit, both the impacts of IVC-backing and SYND-backing are positive and statistically significant (at 1%). The magnitude of the latter is greater than that of IVC-backing, but we cannot reject the null hypothesis of no difference between the two coefficients. The impact of GVC-backing is still negligible, as well as the size and the composition of the syndicate. As regards the negative exits (column IV), there is no impact of VC-backing, whatever the type of VC investor. Still, the yearly number of VC investors exerts a negative impact (statistically significant at 5%), while the institutional heterogeneity of the syndicate positively impacts the likelihood of firm liquidation (statistical significance at 1%). The impact of the investment stage is always positive but negligible, whatever the exit type.

6.5. Distance

Finally we control for the distance between the VC investors and portfolio companies. VC investors prefer to target portfolio companies which are located closer (Lerner, 1995). This way, it is easier for VC investors monitor portfolio companies and perform their value-adding activities. So, as suggested by Sørensen (2007), distance is not independent of the investment outcome. Also in this case, if the different types of VC investors systematically choose companies at a certain distance from their headquarters and there is an alleged positive/negative correlation between the distance and the likelihood of a positive/negative exit, our results in Table 4 could be biased. In order to control for this potential omitted variable bias, we inserted a continuous variable (*Distance*) that measures the geographic distance between the lead investor of the first VC investment and the target company (in kilometers). This variable is set to zero for all non VC-backed companies.[20] The results are shown in Table 10 (columns V and VI) and are in line with those exposed in Table 4. As regards the likelihood of a positive exit (column V), the impact of IVC-backing is positive and statistically significant at 1%. While, the impact of SYND-backing is positive and statistically significant (at 5%), and shows a magnitude greater than that of IVC-backing. Also in this case, we cannot reject the null hypothesis of no difference between the two coefficients. The impact of GVC-backing is still negligible, as well as the size and the institutional heterogeneity of the syndicate. As regards the negative exits (column VI), there is no impact of all types of VC-backing. Still, the yearly number of VC investors exerts a negative impact (statistically significant at 5%), while the composition of the syndicate has a positive and statistically significant impact (at 1%). The impact of the distance is always negligible, whatever the exit type, even though the sign of the coefficient is the opposite: positive for positive exits and negative for firm liquidations.

7. Concluding Remarks

Prior research indicates that different types of VC investors have a different impact on the performance of their portfolio companies. Despite the high presence of GVC funds in Europe, there is a dearth of contributions evaluating the performance of this specific type of investor. In this work, using a large representative sample of European VC-backed and non-VC backed companies observed from 1991 to 2010, we have compared the exit performance of GVC investors with the one of IVC funds and mixed IVC-GVC syndicates, controlling for the yearly size and institutional heterogeneity of the syndicates.

Our econometric results show that IVC-backed companies have a higher likelihood to reach a positive exit (IPO or trade-sale) than GVC-backed ones. More interestingly,

[20] As robustness check, we also set such variable for all non VC-backed companies to the maximum distance included in the sample. Results are available upon request from the authors.

mixed IVC-GVC syndicated investments lead to a higher (but not statistically different) likelihood of a positive exit than that of IVC-backing. This positive impact of IVC-GVC syndicates is not found to be influenced by the composition of the syndicate in terms of size and institutional heterogeneity. Our findings are robust to several robustness checks - controlling for endogeneity concerns, selection bias, omitted variables bias, legal and institutional differences across countries and over time through several econometric techniques - and alternative explanations.

These results have important policy implications. First, our analysis sheds a negative light on the “go it alone” strategy of the European GVC funds. In doing so, our study defines precise boundaries on the role of the State as active venture capitalist. In fact, there is a positive economically and statistically relevant effect on the exit performance of young high-tech companies when governmental bodies syndicate with IVCs, whichever the size and the composition of the syndicate. Fortunately, recent European policy initiatives (e.g., the EU framework programme “Horizon 2020”) seem to go exactly this way through the pursuit of public-private partnerships. Our findings totally support this view.

However, our findings also contain a warning for the set-up of this typology of partnerships. In fact, echoing Chahine et al. (2012), our results indicate that the increase of the institutional heterogeneity in VC syndicates may increase the odds of portfolio companies’ liquidation. This is consistent with the fact that heterogeneous investors have different objectives which may lead to principal-principal conflicts (Colombo et al., 2014). Therefore, if IVC-GVC syndicates are found to be beneficial on the one side (i.e., favoring an exit through an IPO or a trade sale), the government and the independent venture capital investor should always remind to keep the institutional heterogeneity of the syndicate at a manageable level in order to limit negative side-effects.

To conclude, this work aimed at offering a general assessment on the performance of GVCs and IVCs and their syndicated activities in the European VC market. Of course, much remains to be investigated and several research directions might be undertaken. For example, future research could deepen the diversity among VC syndicate members, exploring different dimensions than the institutional one investigated here. An interesting element to bring into the analysis could be the reputation of VC syndicate members.

Furthermore, the heterogeneity of the GVC funds across European countries could be explored in terms of sources of financing, internal organization, objectives and selection of portfolio companies. This way, it would be possible to further understand the conditions under which GVCs play an important role for the development of the VC market.

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Table 1. IVC-, GVC-, and SYND-backed companies across countries and industries

	IVC-backed companies		**GVC-backed companies**		**SYND-backed companies**	
	N.	%	N.	%	N.	%
Country						
Belgium	40	9.52	16	12.60	9	14.52
Finland	38	9.05	21	16.54	7	11.29
France	58	13.81	17	13.39	22	35.48
Germany	83	19.76	21	16.54	11	17.74
Italy	41	9.76	10	7.87	3	4.84
Spain	32	7.62	31	24.41	2	3.23
United Kingdom	128	30.48	11	8.66	8	12.90
Total	**420**	**100.00**	**127**	**100.00**	**62**	**100.00**
Industry						
ICT manufacturing	77	18.33	22	17.32	10	16.13
TLC	28	6.67	6	4.72	2	3.23
Internet	57	13.57	9	7.09	3	4.84
Software	167	39.76	41	32.28	31	50.00
Biotechnology & Pharmaceutical	77	18.33	35	27.56	15	24.19
Other	14	3.33	14	11.02	1	1.61
Total	**420**	**100.00**	**127**	**100.00**	**62**	**100.00**

Legend: the sample includes VC-backed companies that enter the VICO dataset between 1984 and 2004 that first receive VC funding in the year they enter the VICO dataset (if such year is not before 1994; see Section 3.1) or in any subsequent year. In columns 1, 3 and 5, the number of IVC-backed companies, GVC-backed companies and SYND-backed companies, according to country and industry. In columns 2, 4 and 6, the percentage of IVC-backed companies (calculated on the total number of IVC-backed companies), the percentage of GVC-backed companies (calculated on the total number of GVC-backed companies), and the percentage of SYND-backed companies (calculated on the total number of SYND-backed companies), according to country and industry. NACE codes of the industries are: ICT manufacturing (30.02, 32, 33); TLC (64.2); Internet (72.60); Software (72.2); Biotech & Pharmaceutical (24.4, 73.1); Other: Robotics (29.5), Aerospace (35.5), and other industries not explicitly included in the NACE classification: Energy and Nanotech.

Table 2. Positive and negative exits across types of VC investors

	IPOs or trade-sales		Liquidations		Binomial proportions test
	N.	%	N.	%	Z
Type of VC investor					
IVC	80	74.77	71	69.61	0.8325
GVC	12	11.21	22	21.57	-2.0272**
SYND	15	14.02	9	8.82	1.1775
Total	**107**	**100.00**	**102**	**100.00**	

Legend: the sample includes VC-backed companies that enter the VICO dataset between 1984 and 2004 that first receive VC funding in the year they enter the VICO dataset (if such year is not before 1994; see Section 3.1) or in any subsequent year. In columns 1 and 3, the number of companies that positively (went public or were acquired) or negatively exited, according to the type of VC-backing. In columns 2 and 4, the percentage of companies that positively exited (calculated on the total number of companies that went public or were acquired) and the percentage of companies that negatively exited (calculated on the total number of liquidated companies), according to the type of VC-backing. In column 5, Z statistic of binomial proportions test is reported. For each row, Z is equal to $(p_1-p_2)/\sqrt{[p*(1-p)*(1/N_1+1/N_2)]}$, where x_1 is equal to the number of firms that went public or were acquired; x_2 is equal to the number of firms that were liquidated; N_1 is equal to the total number of firms that went public or were acquired; N_2 is equal to the total number of firms that were liquidated; p_1 is the ratio between the number of firms that went public or were acquired and the total number of firms that went public or were acquired; p_2 is the ratio between the number of firms that were liquidated and the total number of firms that were liquidated; p is equal to $(x_1+x_2)/(N_1+N_2)$. Z can be approximated with a standard normal distribution given that x_1, x_2, (N_1-x_1), and (N_2-x_2) are all larger than 5.

Table 3. Descriptive statistics

Panel A: IVC-backed companies				
	N. Companies	**Mean**	**Median**	**St. dev.**
VC Size	420	1.9742	1	1.4733
VC Diversity	420	1.3513	1	0.6150
Age	420	6.7729	6	4.1138
Bubble	420	0.4215	0	0.4939
Size	375	35.9546	18	53.0045
ProfitMargin	284	-8.8699	-0.1618	98.2808
TimeFromVC	420	5.5839	5	3.2789
PatentStock	420	0.3703	0	3.5657

Panel B: GVC-backed companies				
	N. Companies	**Mean**	**Median**	**St. dev.**
VC Size	127	1.4208	1	0.8928
VC Diversity	127	1.2417	1	0.5488
Age	127	7.3063	7	4.5329
Bubble	127	0.1597	0	0.3664
Size	116	26.2459	11	48.2168
ProfitMargin	89	-2.8822	0	16.6602
TimeFromVC	127	6.2368	6	3.8252
PatentStock	127	0.6629	0	1.3624

Panel C: SYND-backed companies				
	N. Companies	**Mean**	**Median**	**St. dev.**
VC Size	62	3.3087	3	2.2836
VC Diversity	62	2.0537	2	0.8036
Age	62	7.0152	7	4.2099
Bubble	62	0.3875	0	0.4876
Size	58	38.6614	22	53.3476
ProfitMargin	44	-31.1921	-1.1041	136.7389
TimeFromVC	62	5.5736	5	3.1971
PatentStock	62	1.9199	0	3.3370

Panel D: Non VC-backed companies				
	N. Companies	**Mean**	**Median**	**St. dev.**
Age	7591	6.9007	6	5.0696
Size	7185	23.5570	6	56.1278
ProfitMargin	5868	-1.2492	0.0211	44.1510
PatentStock	7591	0.1581	0	2.5950

Legend: *VC size* represents the yearly number of VC investors backing the firm at time t-1. *VC diversity* looks at the VC affiliation (i.e., independent, corporate, bank-affiliated, university-sponsored, governmental VC) and counts the number of sub-groupings of each VC type backing the firm at time t-1. *Age* is the logarithm of firm age. *Bubble* is equal to 1 whether the first VC investment was received in the years 1999 or 2000. *Size* is the logarithm of headcount at time t-1. *ProfitMargin* is the ratio net income/sales at time t-1. *TimeFromVC* is the time elapsed since the first VC receipt. *PatentStock* is the logarithm of the patent stock at time t-1 (with yearly depreciation=0.15). Sales value and net income have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005).

Table 4. Econometric results

	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION
	I	II	III	IV
IVC	2.7062*** (0.8325)	1.5981 (0.7481)	2.4242*** (0.6858)	1.2484 (0.5613)
GVC	1.6567 (0.9555)	1.5017 (1.0910)	1.5033 (0.8457)	1.1360 (0.7976)
SYND	4.1165*** (2.0384)	2.3809 (1.9250)	3.3304*** (1.5646)	1.5858 (1.3491)
VC Size	-	-	1.1152 (0.2379)	0.3617** (0.1487)
VC Diversity	-	-	1.2341 (0.5224)	6.3751*** (3.2190)
Age	4.7677* (4.3825)	7.1608** (6.3788)	4.9140* (4.4499)	7.5333** (6.6663)
Age^2	0.7159 (0.1560)	0.5631*** (0.1179)	0.7165 (0.1541)	0.5577*** (0.1161)
Bubble	1.1534 (0.3321)	0.6615 (0.3393)	1.0895 (0.3015)	0.6759 (0.3315)
Size	1.3998*** (0.0803)	0.8877*** (0.0410)	1.4034*** (0.0805)	0.8884** (0.0411)
ProfitMargin	1.0086** (0.0039)	1.0007 (0.0008)	1.0104** (0.0042)	1.0006 (0.0009)
TimeFromVC	1.0876** (0.0438)	0.9984 (0.0648)	1.0930** (0.0412)	1.0091 (0.0592)
PatentStock	1.2648** (0.1484)	0.8147 (0.1667)	1.2147 (0.1445)	0.8103 (0.1661)
Country dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Obs.	37048	37048	37048	37048
Groups	5901	5901	5901	5901
Pseudo R^2	0.1354	0.1354	0.1378	0.1378
Log pseudolikelihood	-2562.5352	-2562.5352	-2555.5893	-2555.5893

Legend: estimates are derived from multinomial logit regressions with standard errors robust to heteroskedasticity through the Huber-White method and serial correlation within portfolio companies. In columns I and III, results related to the likelihood of a positive exit (IPO or trade-sale). In columns II and IV, results related to the likelihood of a negative exit (liquidation). Relative-risk ratios are reported. *IVC* is a dummy variable that equals one for the years after obtaining the first VC investment by an IVC investor and zero otherwise. *GVC* is a dummy variable that equals one for the years after obtaining the first VC investment by a GVC investor and zero otherwise. *SYND* is a dummy variable that equals one for the years after obtaining the first VC investment by a mixed IVC-GVC syndicate and zero otherwise. *VC size* represents the yearly number of VC investors backing the firm at time t-1. *VC diversity* looks at the VC affiliation (i.e., independent, corporate, bank-affiliated, university-sponsored, governmental VC) and counts the number of sub-groupings of each VC type backing the firm at time t-1. *Age* is the logarithm of firm age. *Bubble* is equal to 1 whether the first VC investment was received in the years 1999 or 2000. *Size* is the logarithm of headcount at time t-1. *ProfitMargin* is the ratio net income/sales at time t-1. *TimeFromVC* is the time elapsed since the first VC receipt. *PatentStock* is the logarithm of the patent stock at time t-1 (with yearly depreciation=0.15). Sales value and net income have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005). Country, industry and time dummies are included in the estimates (coefficients are omitted in the table). All regressions are estimated with an intercept term. Standard errors in round brackets. * $p < .10$; ** $p < .05$; *** $p < .01$.

Table 5. Selection bias and endogeneity issues: firm quality

	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION
	I	II	III	IV
IVC	2.8796*** (0.8249)	1.3996 (0.6397)	2.3338*** (0.6727)	1.2921 (0.5830)
GVC	1.7039 (0.9739)	1.2374 (0.9065)	1.4727 (0.8321)	1.0974 (0.7649)
SYND	4.0826*** (1.9505)	2.0498 (1.8182)	3.3428*** (1.5494)	1.5535 (1.3189)
VC Size	1.1139 (0.2493)	0.2077** (0.1355)	1.1124 (0.2380)	0.3613** (0.1496)
VC Diversity	1.2344 (0.5530)	11.8638*** (8.7295)	1.2663 (0.5352)	6.3623*** (3.2154)
Age	3.5113 (4.5306)	11.5174** (12.7117)	4.3238 (3.9234)	8.2027** (7.7567)
Age^2	0.7660 (0.2255)	0.5048*** (0.1273)	0.7421 (0.1606)	0.5496*** (0.1219)
Bubble	1.0147 (0.2836)	0.4867 (0.2666)	1.0560 (0.2994)	0.6824 (0.3357)
Size	1.3758*** (0.0825)	0.8788*** (0.0419)	1.3774*** (0.0807)	0.9012** (0.0439)
ProfitMargin	1.0088* (0.0046)	1.0014 (0.0012)	1.0101** (0.0041)	1.0006 (0.0008)
TimeFromVC	1.0817** (0.0419)	1.0067 (0.0624)	1.0957** (0.0419)	1.0117 (0.0595)
PatentStock	1.2024 (0.1454)	0.8015 (0.1717)	1.2186 (0.1482)	0.8232 (0.1684)
PastSalesGrowth	1.0001 (0.0003)	1.0000 (0.0000)	-	-
ITA	-	-	1.0456 (0.5589)	1.2456 (0.4513)
Country dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Obs.	32411	32411	36094	36094
Groups	5615	5615	5835	5835
Pseudo R^2	0.1334	0.1334	0.1322	0.1322
Log pseudolikelihood	-2389.4234	-2389.4234	-2432.6297	-2432.6297

Legend: estimates are derived from multinomial logit regressions with standard errors robust to heteroskedasticity through the Huber-White method and serial correlation within portfolio companies. In columns I and III, results related to the likelihood of a positive exit (IPO or trade-sale). In columns II and IV, results related to the likelihood of a negative exit (liquidation). Relative-risk ratios are reported. *IVC* is a dummy variable that equals one for the years after obtaining the first VC investment by an IVC investor and zero otherwise. *GVC* is a dummy variable that equals one for the years after obtaining the first VC investment by a GVC investor and zero otherwise. *SYND* is a dummy variable that equals one for the years after obtaining the first VC investment by a mixed IVC-GVC syndicate and zero otherwise. *VC size* represents the yearly number of VC investors backing the firm at time t-1. *VC diversity* looks at the VC affiliation (i.e., independent, corporate, bank-affiliated, university-sponsored, governmental VC) and counts the number of sub-groupings of each VC type backing the firm at time t-1. *Age* is the logarithm of firm age. *Bubble* is equal to 1 whether the first VC investment was received in the years 1999 or 2000. *Size* is the logarithm of headcount at time t-1. *ProfitMargin* is the ratio net income/sales at time t-1. *TimeFromVC* is the time elapsed since the first VC receipt. *PatentStock* is the logarithm of the patent stock at time t-1 (with yearly depreciation=0.15). *PastSalesGrowth* is the growth in sales value from the time t-2 to the time t-1. *ITA* is the ratio between intangible assets and total assets at time t-1. Sales value, net income, total assets and intangible assets have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005). Country, industry and time dummies are included in the estimates (coefficients are omitted in the table). All regressions are estimated with an intercept term. Standard errors in round brackets. * $p < .10$; ** $p < .05$; *** $p < .01$.

Table 6. Selection bias and endogeneity issues: panel multinomial logit with random effects, panel probit models on matched samples, and Instrumental Variables (IV) linear probability models

	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION
	I	II	III	IV	V	VI
IVC	0.8457*** (0.3179)	0.1070 (0.4087)	0.7488*** (0.2420)	0.2572 (0.4900)	0.2050* (0.1191)	0.0169 (0.1287)
GVC	-0.2966 (0.5478)	-0.9518 (0.6813)	0.2322 (0.4641)	0.3247 (0.6595)	0.2626 (0.1952)	0.2729 (0.2592)
SYND	0.9799** (0.4757)	-0.0463 (0.8058)	0.7991** (0.3639)	1.3446** (0.5483)	0.5871* (0.3367)	0.5993 (0.4693)
VC Size	0.1311 (0.1764)	-0.8125 (0.6321)	0.0620 (0.1497)	-2.0097*** (0.6057)	-	-
VC Diversity	0.1624 (0.3712)	1.5319* (0.7878)	0.0349 (0.2634)	2.1571** (0.8731)	-	-
Age	1.4455 (0.9990)	3.8022*** (0.8744)	2.5325** (1.1590)	1.5702 (1.6904)	0.0111 (0.0119)	0.0414*** (0.0131)
Age^2	-0.2825 (0.2348)	-0.9119*** (0.2098)	-0.6593** (0.3061)	-0.4388 (0.4498)	-0.0011 (0.0026)	-0.0100*** (0.0029)
Bubble	0.2568 (0.2634)	-0.5709 (0.4368)	0.2383 (0.1892)	-0.8682* (0.4637)	-0.0540 (0.0342)	-0.0105 (0.0363)
Size	0.2956*** (0.0513)	-0.0914* (0.0466)	0.1113 (0.0959)	0.0412 (0.0881)	0.0020** (0.0008)	-0.0015** (0.0007)
ProfitMargin	0.0090 (0.0086)	0.0002 (0.0017)	0.0026 (0.0016)	0.0080 (0.0052)	0.0001** (0.0000)	0.0001 (0.0000)
TimeFromVC	0.1023*** (0.0391)	0.0692 (0.0534)	-0.0144 (0.0482)	0.0038 (0.0581)	-0.0258 (0.0172)	-0.0188 (0.0205)
PatentStock	0.2064* (0.1203)	-0.2016 (0.1994)	0.3998** (0.1619)	-0.0874 (0.2379)	-0.0177 (0.0130)	-0.0180 (0.0134)
Country dummies	No	No	Yes	Yes	Yes	Yes
Industry dummies	No	No	Yes	Yes	Yes	Yes
Year dummies	No	No	Yes	Yes	Yes	Yes
Obs.	37048	37048	2783	3203	19353	22537
Groups	-	-	355	393	-	-
Adjusted R^2	-	-	-	-	-	-
Log pseudolikelihood	-2859.4617	-2859.4617	-	-	-	-
F(IVC)	-	-	-	-	317.39	366.09
F(PVC)	-	-	-	-	182.22	200.35
F(SYND)	-	-	-	-	61.27	64.88

Legend: estimates are derived from multilevel latent variable models for unordered categorical responses, in which the latent variables are modeled as random effects (columns I and II), panel probit models after performing separately for IVC-backed, GVC-backed or SYND-backed companies a one-to-one propensity score matching without replacement in the year of the first VC investment (columns III and IV), and pooled Instrumental Variables (IV) linear probability models with standard errors clustered at portfolio company-level (columns V and VI). In the last rows of the table (columns V and VI), we reported the F statistics related to the first-stage regressions of the IV procedure. In columns I, III and V, results related to the likelihood of a positive exit (IPO or trade-sale); in columns II, IV and VI, results related to the likelihood of a negative exit (liquidation). Estimated coefficients (and not relative-risk ratios) are reported. *IVC* is a dummy variable that equals one for the years after obtaining the first VC investment by an IVC investor and zero otherwise. *GVC* is a dummy variable that equals one for the years after obtaining the first VC investment by a GVC investor and zero otherwise. *SYND* is a dummy variable that equals one for the years after obtaining the first VC investment by a mixed IVC-GVC syndicate and zero otherwise. *VC size* represents the yearly number of VC investors backing the firm at time t-1. *VC diversity* looks at the VC affiliation (i.e., independent, corporate, bank-affiliated, university-sponsored, governmental VC) and counts the number of sub-groupings of each VC type backing the firm at time t-1. *Age* is the logarithm of firm age. *Bubble* is equal to 1 whether the first VC investment was received in the years 1999 or 2000. *Size* is the logarithm of headcount at time t-1. *ProfitMargin* is the ratio net income/sales at time t-1. *TimeFromVC* is the time elapsed since the first VC receipt. *PatentStock* is the logarithm of the patent stock at time t-1 (with yearly depreciation=0.15). Sales value and net income have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005). Country, industry and time dummies are included in the estimates (coefficients are omitted in the table). All regressions are estimated with an intercept term. Standard errors in round brackets. * p < .10; ** p < .05; *** p < .01.

Table 7. Robustness checks: methodologies

	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION
	I	II	III	IV
IVC	0.4851*** (0.1706)	0.1171 (0.2443)	0.1204*** (0.0304)	0.0132 (0.0519)
GVC	0.1650 (0.3248)	0.0704 (0.3686)	0.1091* (0.0571)	0.0161 (0.0814)
SYND	0.7119** (0.2828)	0.3617 (0.4466)	0.1069** (0.0467)	0.0878 (0.0894)
VC Size	0.0553 (0.1324)	-0.6206** (0.2592)	0.0332 (0.0206)	-0.1438** (0.0634)
VC Diversity	0.1626 (0.2572)	1.1186*** (0.3272)	-0.0052 (0.0436)	0.2389*** (0.0713)
Age	1.3109** (0.5453)	1.5809*** (0.5005)	-	-
Age^2	-0.2754** (0.1271)	-0.4273*** (0.1175)	-	-
Bubble	0.0203 (0.1658)	-0.1402 (0.2473)	0.3895 (0.2753)	-0.3439 (0.4944)
Size	0.1937*** (0.0300)	-0.0492* (0.0251)	0.0282*** (0.0057)	-0.0120** (0.0048)
ProfitMargin	0.0056** (0.0026)	0.0004 (0.0005)	0.0008** (0.0003)	0.0001 (0.0001)
TimeFromVC	0.0555** (0.0231)	0.0005 (0.0319)	-0.0005 (0.0035)	-0.0014 (0.0058)
PatentStock	0.0879 (0.0698)	-0.1278 (0.1049)	0.0124 (0.0088)	-0.0149 (0.0204)
Country dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Obs.	37048	37048	37069	37069
Groups	5901	5901	5902	5902
Log pseudolikelihood	-2555.8908	-2555.8908	-1390.5688	-2050.4489

Legend: estimates are derived from multinomial probit regressions with standard errors robust to heteroskedasticity through the Huber-White method and serial correlation within portfolio companies (columns I and II) and semi-parametric Cox-type survival models, in which firm age is the random variable to define the time of 'death', i.e. first exit in a competing risk scenario (columns III and IV). In columns I and III, results related to the likelihood of a positive exit (IPO or trade-sale); in columns II and IV, results related to the likelihood of a negative exit (liquidation). Estimated coefficients (and not relative-risk ratios) are reported. *IVC* is a dummy variable that equals one for the years after obtaining the first VC investment by an IVC investor and zero otherwise. *GVC* is a dummy variable that equals one for the years after obtaining the first VC investment by a GVC investor and zero otherwise. *SYND* is a dummy variable that equals one for the years after obtaining the first VC investment by a mixed IVC-GVC syndicate and zero otherwise. *VC size* represents the yearly number of VC investors backing the firm at time t-1. *VC diversity* looks at the VC affiliation (i.e., independent, corporate, bank-affiliated, university-sponsored, governmental VC) and counts the number of sub-groupings of each VC type backing the firm at time t-1. *Age* is the logarithm of firm age. *Bubble* is equal to 1 whether the first VC investment was received in the years 1999 or 2000. *Size* is the logarithm of headcount at time t-1. *ProfitMargin* is the ratio net income/sales at time t-1. *TimeFromVC* is the time elapsed since the first VC receipt. *PatentStock* is the logarithm of the patent stock at time t-1 (with yearly depreciation=0.15). Sales value and net income have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005). Country, industry and time dummies are included in the estimates (coefficients are omitted in the table). All regressions are estimated with an intercept term. Standard errors in round brackets. * p < .10; ** p < .05; *** p < .01.

Table 8. Robustness checks: operationalization of variables

	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION
	I	II	III	IV	V	VI	VII	VIII	IX	X
IVC	2.4175*** (0.6837)	1.1934 (0.5453)	2.0811*** (0.5782)	1.2457 (0.5711)	1.9398** (0.5363)	1.2669 (0.4942)	2.0107** (0.5825)	1.1168 (0.5135)	2.2908*** (0.6165)	1.3967 (0.5410)
GVC	1.4948 (0.8376)	1.1802 (0.8281)	1.0219 (0.6034)	1.2186 (0.8613)	1.1774 (0.6122)	0.8815 (0.5338)	1.2043 (0.6654)	1.0842 (0.7639)	1.4311 (0.7463)	0.9928 (0.5949)
SYND	3.4152*** (1.5623)	1.5269 (1.2940)	2.3985* (1.1409)	0.8149 (0.8984)	2.3334** (0.9047)	2.2428 (1.3067)	2.5027** (1.1670)	1.6238 (1.3725)	3.0371*** (1.1618)	2.2040 (1.2925)
VC Size	1.1120 (0.2363)	0.3579** (0.1470)	1.1650 (0.2449)	0.3660** (0.1494)	1.3567** (0.2053)	0.4351** (0.1556)	1.2721 (0.2358)	0.2574** (0.1676)	1.2167 (0.2053)	0.4802*** (0.1352)
VC Diversity	1.2399 (0.5252)	6.4690*** (3.2803)	1.2066 (0.4977)	6.4467*** (3.2410)	0.8483 (0.2656)	3.6391*** (1.4980)	0.9741 (0.3639)	8.1037*** (5.8825)	1.0125 (0.3497)	3.6218*** (1.2690)
Age	4.9096* (4.4414)	7.5664** (6.6823)	2.7759 (2.3903)	7.9639** (6.9511)	2.9758 (2.4465)	8.4043*** (5.8489)	2.6644 (2.3540)	7.0239** (5.7783)	5.5992** (4.7017)	8.8671*** (6.5519)
Age^2	0.7169 (0.1540)	0.5572*** (0.1157)	0.8035 (0.1635)	0.5671*** (0.1165)	0.8001 (0.1555)	0.5672*** (0.0942)	0.8201 (0.1705)	0.5803*** (0.1128)	0.6951* (0.1391)	0.5543*** (0.0973)
Bubble	-	-	1.0591 (0.2931)	0.8183 (0.3923)	0.9130 (0.2506)	0.6430 (0.2714)	0.8820 (0.2583)	0.7082 (0.3525)	1.1464 (0.2962)	0.6353 (0.2672)
Bubble 1998-2000	1.1152 (0.3095)	0.8649 (0.3903)	-	-	-	-	-	-	-	-
Size	1.4033*** (0.0805)	0.8877*** (0.0411)	1.4637*** (0.0805)	0.8404*** (0.0394)	1.4818*** (0.0807)	0.7587*** (0.0364)	1.4610*** (0.0817)	0.8280*** (0.0390)	1.4339*** (0.0794)	0.7982*** (0.0383)
ProfitMargin	1.0104** (0.0042)	1.0006 (0.0009)	-	-	-	-	-	-	-	-
Profitability	-	-	1.0516** (0.0222)	1.0031 (0.0028)	-	-	-	-	-	-
EBITDA on Total Assets	-	-	-	-	0.9976 (0.0034)	0.9905** (0.0040)	-	-	-	-
EBITDA on Sales	-	-	-	-	-	-	1.0060*** (0.0020)	1.0006 (0.0009)	-	-
ROA	-	-	-	-	-	-	-	-	0.9950 (0.0039)	0.9924 (0.0051)
TimeFromVC	1.0922** (0.0410)	0.9994 (0.0552)	1.0836** (0.0405)	0.9941 (0.0626)	1.0846** (0.0393)	1.0307 (0.0515)	1.0892** (0.0410)	1.0205 (0.0595)	1.0828** (0.0396)	1.0172 (0.0514)
PatentStock	1.2086 (0.1441)	0.8160 (0.1678)	1.1651 (0.1399)	0.7915 (0.1645)	1.2787** (0.1472)	0.8406 (0.1616)	1.1805 (0.1457)	0.8301 (0.1663)	1.3070** (0.1474)	0.8571 (0.1600)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	37048	37048	37194	37194	41650	41650	36842	36842	42014	42014
Groups	5901	5901	5956	5956	6348	6348	5952	5952	6305	6305
Pseudo R^2	0.1377	0.1377	0.1362	0.1362	0.1285	0.1285	0.1340	0.1340	0.1295	0.1295
Log pseudolikelihood	-2555.8849	-2555.8849	-2721.4855	-2721.4855	-3218.7365	-3218.7365	-2726.4466	-2726.4466	-3083.0822	-3083.0822

Legend: estimates are derived from multinomial logit regressions with standard errors robust to heteroskedasticity through the Huber-White method and serial correlation within portfolio companies. In columns I, III, V, VI and IX, results related to the likelihood of a positive exit (IPO or trade-sale); in columns II, IV, VI, VIII and X, results related to the likelihood of a negative exit (liquidation). Relative-risk ratios are reported. *IVC* is a dummy variable that equals one for the years after obtaining the first VC investment by an IVC investor and zero otherwise. *GVC* is a dummy variable that equals one for the years after obtaining the first VC investment by a GVC investor and zero otherwise. *SYND* is a dummy variable that equals one for the years after obtaining the first VC investment by a mixed IVC-GVC syndicate and zero otherwise. *VC size* represents the yearly number of VC investors backing the firm at time t-1. *VC diversity* looks at the VC affiliation (i.e., independent, corporate, bank-affiliated, university-sponsored, governmental VC) and counts the number of sub-groupings of each VC type backing the firm at time t-1. *Age* is the logarithm of firm age. *Bubble* is equal to 1 whether the first VC investment was received in the years 1999 or 2000. *Bubble 1998-2000* is equal to 1 whether the first VC investment was received in the years 1998, 1999 or 2000. *Size* is the logarithm of headcount at time t-1. *ProfitMargin* is the ratio net income/sales at time t-1. *Profitability* is the ratio (sales - payroll expenses)/sales value at time t-1. *EBITDA on Total Assets* is the ratio EBITDA/total assets at time t-1. *EBITDA on Sales* is the ratio EBITDA/sales at time t-1. *ROA* is the ratio net income/total assets at time t-1. *TimeFromVC* is the time elapsed since the first VC receipt. *PatentStock* is the logarithm of the patent stock at time t-1 (with yearly depreciation=0.15). Sales value, net income, payroll expenses, EBITDA, and total assets have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005). Country, industry and time dummies are included in the estimates (coefficients are omitted in the table). All regressions are estimated with an intercept term. Standard errors in round brackets. * $p < .10$; ** $p < .05$; *** $p < .01$.

Table 9. Alternative explanations

	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION
	I	II	III	IV
IVC	-	-	2.4326*** (0.6912)	1.2474 (0.5679)
SYND	-	-	3.3561** (1.5854)	1.5926 (1.3619)
IVC_holding	3.1178** (1.5444)	1.5119 (0.9269)	-	-
GVC_holding	1.8014 (2.2024)	1.2014 (1.4575)	-	-
SYND_holding	6.6730*** (4.7390)	0.0000*** (0.000)	-	-
GVC_pre	-	-	1.3704 (0.8153)	0.8894 (0.7532)
IVC_post	-	-	2.4281 (2.9016)	2.0203 (2.1177)
VC Size	1.1527 (0.2594)	0.3530** (0.1447)	1.1182 (0.2381)	0.3673** (0.1482)
VC Diversity	0.7973 (0.4538)	6.2804*** (3.2851)	1.2223 (0.5165)	6.1923*** (3.1342)
Age	5.2726* (4.7825)	7.5312** (6.6308)	4.9035* (4.4439)	7.4744** (6.6164)
Age^2	0.6975* (0.1501)	0.5574*** (0.1154)	0.7168 (0.1543)	0.5588*** (0.1163)
Bubble	1.4005 (0.3654)	0.7018 (0.3389)	1.0898 (0.3022)	0.6755 (0.3327)
Size	1.4208*** (0.800)	0.8877** (0.0412)	1.4031*** (0.0805)	0.8883** (0.0411)
ProfitMargin	1.0111*** (0.0042)	1.0006 (0.0009)	1.0105** (0.0042)	1.0006 (0.0009)
TimeFromVC	1.1612*** (0.0365)	1.0276 (0.0417)	1.0929** (0.0414)	1.0102 (0.0605)
PatentStock	1.2280* (0.1456)	0.8290 (0.1670)	1.2143 (0.1448)	0.8095 (0.1647)
Country dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Obs.	37048	37048	37048	37048
Groups	5901	5901	5901	5901
Pseudo R^2	0.1375	0.1375	0.1379	0.1379
Log pseudolikelihood	-2556.4191	-2556.4191	-2555.3026	-2555.3026

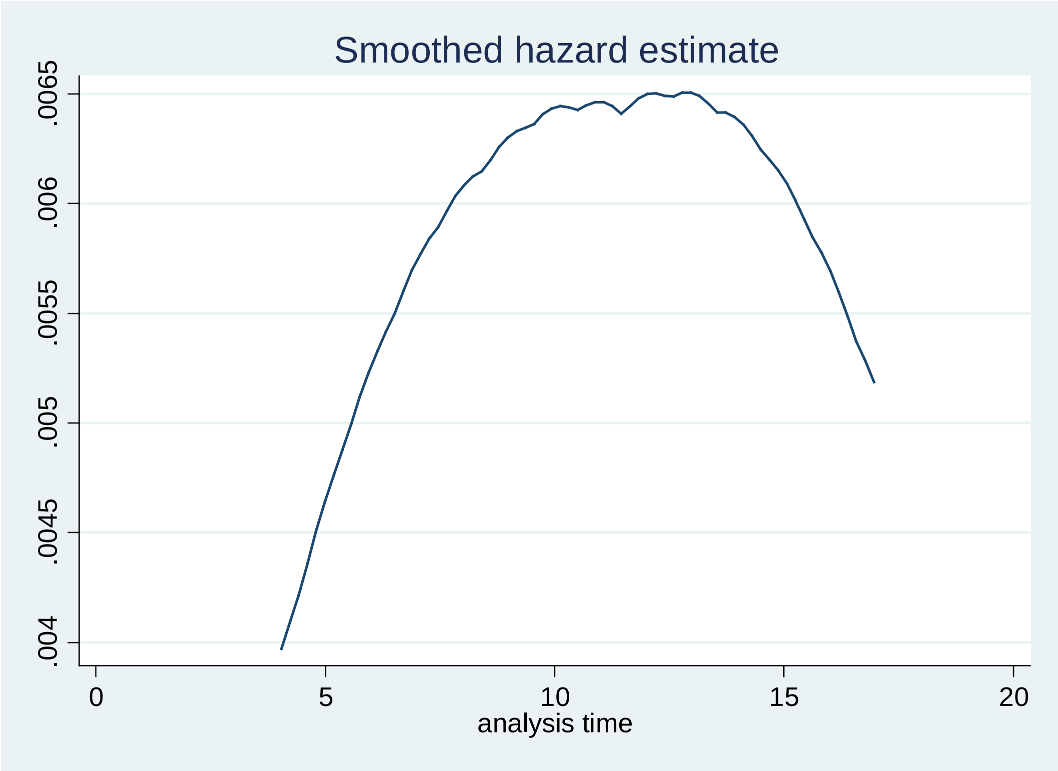
Legend: estimates are derived from multinomial logit regressions with standard errors robust to heteroskedasticity through the Huber-White method and serial correlation within portfolio companies. In columns I and III, results related to the likelihood of a positive exit (IPO or trade-sale); in columns II and IV, results related to the likelihood of a negative exit (liquidation). Relative-risk ratios are reported. *IVC* is a dummy variable that equals one for the years after obtaining the first VC investment by an IVC investor and zero otherwise. *SYND* is a dummy variable that equals one for the years after obtaining the first VC investment by a mixed IVC-GVC syndicate and zero otherwise. *IVC_holding* is a dummy variable that equals one for the years after obtaining the first VC investment by an IVC investor until the end of the IVC investor's holding period and zero otherwise. *GVC_holding* is a dummy variable that equals one for the years after obtaining the first VC investment by a GVC investor until the end of the GVC investor's holding period and zero otherwise. *SYND_holding* is a dummy variable that equals one for the years after obtaining the first VC investment by a mixed IVC-GVC syndicate until the end of the mixed IVC-GVC syndicate's holding period and zero otherwise. *GVC_pre* is a dummy variable that equals one for the years after obtaining the first VC investment by a GVC investor until the (potential) receipt of a subsequent IVC investment and zero otherwise. *IVC_post* is a dummy variable that equals one from the year of a subsequent IVC investment, which occurs after the first GVC investment, and zero otherwise. *VC size* represents the yearly number of VC investors backing the firm at time t-1. *VC diversity* looks at the VC affiliation (i.e., independent, corporate, bank-affiliated, university-sponsored, governmental VC) and counts the number of sub-groupings of each VC type backing the firm at time t-1. *Age* is the logarithm of firm age. *Bubble* is equal to 1 whether the first VC investment was received in the years 1999 or 2000. *Size* is the logarithm of headcount at time t-1. *ProfitMargin* is the ratio net income/sales at time t-1. *TimeFromVC* is the time elapsed since the first VC receipt. *PatentStock* is the logarithm of the patent stock at time t-1 (with yearly depreciation=0.15). Sales value and net income have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005). Country, industry and time dummies are included in the estimates (coefficients are omitted in the table). All regressions are estimated with an intercept term. Standard errors in round brackets. * $p < .10$; ** $p < .05$; *** $p < .01$.

Table 10. Alternative explanations

	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION	IPO/ACQUISITION	LIQUIDATION
	I	II	III	IV	V	VI
IVC	2.6842*** (0.8834)	1.2520 (0.5779)	2.2065*** (0.6582)	1.1343 (0.4961)	2.6687*** (0.9275)	1.1204 (0.5931)
GVC	2.2899 (1.4248)	1.3860 (0.9855)	1.3253 (0.7757)	0.9823 (0.6747)	1.1063 (0.8189)	1.0843 (0.8501)
SYND	2.9200* (1.6000)	1.9926 (1.7244)	3.3308*** (1.5067)	1.4294 (1.2431)	3.7693** (2.3542)	0.9302 (1.0602)
VC Size	1.2630 (0.2482)	0.2388** (0.1568)	1.0971 (0.2350)	0.3618** (0.1497)	1.0371 (0.2566)	0.3079** (0.1458)
VC Diversity	0.8892 (0.3635)	9.7933*** (7.0612)	1.2222 (0.5164)	6.1190*** (3.1051)	1.2878 (0.6422)	8.9983*** (5.2935)
Age	1.7530 (1.8622)	5.7847 (6.2506)	5.2806* (4.8235)	7.8755** (7.0035)	6.2855** (5.8721)	8.0461** (7.1514)
Age^2	0.9188 (0.2305)	0.5884** (0.1473)	0.7199 (0.1559)	0.5552*** (0.1158)	0.6704* (0.1486)	0.5475*** (0.1144)
Bubble	0.9591 (0.3122)	0.5557 (0.3166)	1.0656 (0.2936)	0.6587 (0.3164)	1.2122 (0.3844)	0.6905 (0.3555)
Size	1.4972*** (0.0994)	0.9086* (0.0459)	1.4067*** (0.0807)	0.8888** (0.0411)	1.4271*** (0.0849)	0.8860** (0.0417)
ProfitMargin	1.0093** (0.0047)	1.0002 (0.0005)	1.0114*** (0.0042)	1.0007 (0.0009)	1.0082** (0.0037)	1.0004 (0.0007)
TimeFromVC	1.1063** (0.0470)	1.0212 (0.0597)	1.0577 (0.0405)	0.9805 (0.0649)	1.1058** (0.0522)	1.0406 (0.0710)
PatentStock	1.1640 (0.1530)	0.7180 (0.1615)	1.1854 (0.1432)	0.8028 (0.1649)	1.0737 (0.1375)	0.8173 (0.1694)
DTA	1.0170*** (0.0058)	1.0029 (0.0114)	-	-	-	-
NCFTA	0.9895 (0.0073)	1.0599 (0.1222)	-	-	-	-
Earlystage	-	-	1.6900 (0.5791)	1.5280 (0.5747)	-	-
Distance	-	-	-	-	1.0001 (0.0002)	0.9997 (0.0002)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	29206	29206	37048	37048	36404	36404
Groups	5164	5164	5901	5901	5788	5788
Pseudo R^2	0.1332	0.1332	0.1384	0.1384	0.1408	0.1408
Log pseudolikelihood	-2018.5674	-2018.5674	-2553.6367	-2553.6367	-2495.0815	-2495.0815

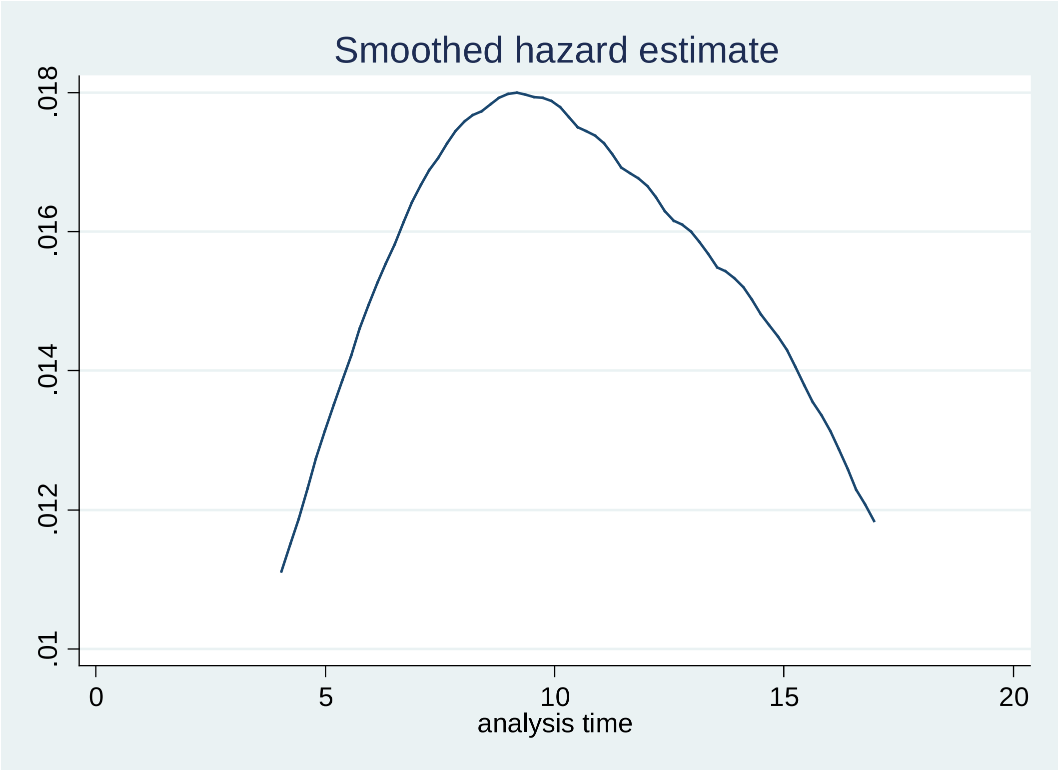
Legend: estimates are derived from multinomial logit regressions with standard errors robust to heteroskedasticity through the Huber-White method and serial correlation within portfolio companies. In columns I, III and V, results related to the likelihood of a positive exit (IPO or trade-sale); in columns II, IV and VI, results related to the likelihood of a negative exit (liquidation). Relative-risk ratios are reported. *IVC* is a dummy variable that equals one for the years after obtaining the first VC investment by an IVC investor and zero otherwise. *GVC* is a dummy variable that equals one for the years after obtaining the first VC investment by a GVC investor and zero otherwise. *SYND* is a dummy variable that equals one for the years after obtaining the first VC investment by a mixed IVC-GVC syndicate and zero otherwise. *VC size* represents the yearly number of VC investors backing the firm at time t-1. *VC diversity* looks at the VC affiliation (i.e., independent, corporate, bank-affiliated, university-sponsored, governmental VC) and counts the number of sub-groupings of each VC type backing the firm at time t-1. *Age* is the logarithm of firm age. *Bubble* is equal to 1 whether the first VC investment was received in the year 1999 or 2000. *Size* is the logarithm of headcount at time t-1. *ProfitMargin* is the ratio net income/sales at time t-1. *TimeFromVC* is the time elapsed since the first VC receipt. *PatentStock* is the logarithm of the patent stock at time t-1 (with yearly depreciation=0.15). *DTA* is the ratio between short-term debt and total assets at time t-1. *NCFTA* is the ratio between net cash flow and total assets at time t-1. *Earlystage* is a dummy variable that equals one for the companies which obtained the first VC investment in the first two years after firm foundation and zero otherwise (the variable is set to zero for all non VC-backed companies). *Distance* measures the geographic distance between the lead investor of the first VC investment and the target company (in kilometers) (the variable is set to zero for all non VC-backed companies). Sales value, net income, short-term debt, total assets, and net cash flow have been deflated by the Consumer Price Index (source: Eurostat; reference year: 2005). Country, industry and time dummies are included in the estimates (coefficients are omitted in the table). All regressions are estimated with an intercept term. Standard errors in round brackets. * $p < .10$; ** $p < .05$; *** $p < .01$.

Figure 1. Estimates of the non-parametric hazard function of a positive outcome



Legend: on the horizontal and vertical axes, there are the firm age and the estimated unconditional likelihood of a positive exit, respectively. The smoothed hazard function is the unconditional instantaneous probability of a positive exit (IPO or trade-sale), provided that this has not occurred by *t*. The smoothed hazard function is estimated through a semi-parametric approach (Cox, 1972).

Figure 2. Estimates of the non-parametric hazard function of a negative outcome



Legend: on the horizontal and vertical axes, there are the firm age and the estimated unconditional likelihood of a negative exit, respectively. The smoothed hazard function is the unconditional instantaneous probability of a negative exit (liquidation), provided that this has not occurred by *t*. The smoothed hazard function is estimated through a semi-parametric approach (Cox, 1972).