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# Government, venture capital and the growth of European high-tech entrepreneurial firms

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ABSTRACT

Using a new European Union-sponsored firm-level longitudinal dataset, we assess the impact of government-managed (GVC) and independent venture capital (IVC) funds on the sales and employee growth of European high-tech entrepreneurial firms. Our results show that the main statistically robust and economically relevant positive effect is exerted by IVC investors on firm sales growth. Conversely, the impact of GVC alone appears to be negligible. We also find a positive and statistically significant impact of syndicated investments by both types of investors on firm sales growth, but only when led by IVC investors. Our results remain stable after controlling for endogeneity, survivorship bias, reverse causality, anticipation effects, legal and institutional differences across countries and over time and are stable with respect to potential non-linear effects of age and size of entrepreneurial firms. Overall, our analysis casts doubt on the ability of governments to support high-tech entrepreneurial firms through a direct and active involvement in VC markets.

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## 1. Introduction

The gap in public and private R&D spending is reputed by policymakers to be one of the main factors that is responsible for the slower growth rate that European economies have been experiencing with respect to international competitors. Although the relationship between R&D and economic growth is far from finding full support in the scientific literature and cannot be considered to be automatic (see, for example, the Swedish case and the R&D-growth paradox discussed in Dosi et al., 2006, and Ejermo et al., 2011), the need to increase R&D spending has been at the center of the Communitarian policies since the Lisbon 2000 strategy. In this respect, one important cause that is individuated by the European Commission for explaining the European R&D gap is the low presence of high-tech rapid-growth entrepreneurial firms on the old continent. In the words of the Europe 2020 agenda (European Commission, 2010: p. 10), 'R&D spending in Europe is below 2%, compared to 2.6% in the US. [. . .] Our smaller share of high-tech firms explains half of our gap with the US'.

One widely shared belief is that the creation of a florid pan-European venture capital (VC) market is a fundamental pre-requisite to bridging the above-mentioned gap and increasing the European Union (EU) performances in terms of innovation (Kortum and Lerner, 2000), job creation (Puri and Zarutskie, 2012) and economic growth (Samila and Sorenson, 2011).

However, the development of VC markets in the European Member States has been dramatically different from the development that is experienced in the US. The ratio between VC and private equity (PE) investments was estimated in 2009 to be 17% in Europe and 67% in the US,[1] and the overall value of the VC investments over the GDP is nearly three times higher in the US than in Europe (Bertoni and Croce, 2011; Croce et al., 2013a). The recent financial crisis has further weakened the EU VC fundraising ability in the subsequent years (Kraemer-Eis and Lang, 2011).

The need for an efficient EU VC market to spur economic growth is well understood at the policy level and has resulted in a series of initiatives (the most important one is the Risk Capital Action Plan in 1998) at various playing field-levels (e.g., measures that aim at increasing stock market openness and/or labor market flexibility or tax incentives), which targeted both the supply of and the demand for VC. According to market operators, even though some structural problems remain (e.g., thin and fragmented exit

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[1] VC investments include seed, early stage and expansion deals. PE investments also include buyout deals (sources: European Venture Capital Association, EVCA; National Venture Capital Association, NVCA).

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markets, limited fundraising ability due to different national regulatory regimes), these attempts contributed to strengthening the EU VC markets, especially after the dot-com bubble (EVCA, 2010). Such policy initiatives also led to a specific peculiarity of the EU context: the relative importance compared to other geographical contexts (the US *in primis*) of governmental VC funds (GVCs) (Leleux and Surlemont, 2003). GVCs are not indirect government support programs to stimulate the supply of VC funds managed by independent companies (IVCs), and they are not public subsidies that are directed toward the assistance of high-tech entrepreneurial firms.[2] Instead, GVCs are defined as funds that are managed by a company that is entirely possessed by governmental bodies.[3] Such funds are intended to complement the thin private supply of VC by entering directly into the VC markets and helping to solve the typical chicken-egg paradox of nascent markets–in which the deal flow is scarce because of a shortage of VC and, at the same time, VC is poorly developed because there are few potential viable targets. Examples of such programs in Europe are several. In Belgium, the Biotech Fonds Vlaanderen was founded by the Flemish government in 1994 with the aim of financing promising biotechnology companies and now is managed by another public body: GIMV. In Finland, SITRA (the Finnish Innovation Fund) was founded in 1967 by the Bank of Finland and now is managed by public bodies that are affiliated with the Finnish Parliament. In the UK, Scottish Enterprise is a public agency (born as a merger of the Scottish Development Agency and the Scottish Training Agency), which is almost fully financed by the Scottish government and selects equity investments in promising start-ups. Public initiatives that fall into the definition of GVC are also quite typical in other European contexts (e.g., France, Germany, Italy, Spain, among others), and they share the same mission of nurturing through public equity(-like) investments the development and growth of interesting business projects.

Despite the numeric relevance of GVCs in Europe and their important degree of syndication and co-financing activities with IVCs, there is a total dearth of contributions that evaluate the role that GVCs play in fostering the growth of high-tech entrepreneurial firms in Europe. In fact, the extant empirical literature has prevalently been devoted to examining the characteristics of specific (extra-European) GVC programs or the moderating role that GVCs exert on the (different from growth) performance of firms backed by private VC funds (Brander et al., 2012). Alternatively, previous studies have adopted a macro perspective that highlighted country-specific policy (Cumming and MacIntosh, 2007b) and institutional factors that are aimed at sustaining the European VC industry (Armour and Cumming, 2006; Da Rin et al., 2006).

The present work aims at reducing the above-mentioned gap. Using the VICO dataset, a novel firm-level longitudinal dataset sponsored by the European Union under the 7° Framework Program (for more details, see the official website at: http://www.vicoproject.org), we assess the impact of GVCs in comparison (and in conjunction) with IVCs on the growth of European high-tech entrepreneurial firms. First, we analyze whether the GVCs and IVCs on their own exert any beneficial effect on the growth of European high-tech entrepreneurial firms. Second, given the existence of co-financing and syndication activities between GVCs and IVCs,[4] we also investigate whether the sequence between the GVC and IVC investments is relevant. In particular, we examine whether significant differences in the firms' growth emerge if a GVC (IVC) investment occurs after an IVC (GVC) investment and whether syndication – the presence of both GVC and IVC in the first VC investment received by a portfolio firm – is otherwise preferable.

The remainder of this paper is organized as follows. Section 2 highlights the background literature. Section 3 describes the data. Section 4 explains the methodology. Section 5 presents the results. Section 6 shows additional evidence and robustness tests. Section 7 concludes.

## 2. Background literature

### 2.1. VC and firm growth

VC is reputed to be the most tailored financing mode for the growth of high-tech entrepreneurial firms, as recognized by academics (Gompers and Lerner, 2001) and (European) policymakers (EU Economic Recovery Plan; European Council, 2008). The available empirical evidence points steadily toward a positive impact of VC on firm growth (e.g., Bertoni et al., 2011; Puri and Zarutskie, 2012). Typically, there are four main reasons that are advocated in support of this positive impact. First, VC investors (VCs) are better at screening entrepreneurial firms that have high-growth potential than are other capital market operators (Sahlman, 1990), and they provide firms with the financial resources that firms need. Second, VCs 'add value' to portfolio companies through the provision of both managerial skills and competencies (Hellmann and Puri, 2002) and the monitoring activity of their managerial conducts and results (Lerner, 1995). Third, VC endorsement represents a 'signal' of the quality of the portfolio firms to uninformed third parties. Hence, VC-backed firms access external resources and competencies that would be out of reach without VC endorsement (Hsu, 2006). Finally, VC-backed firms benefit from the network of business contacts (e.g., suppliers, customers, institutional investors) of their VCs (Hochberg et al., 2007).

### 2.2. Typology of VC and firm growth: IVC and GVC

VCs diverge along several dimensions, including investment targets, screening evaluation methods, skills and competencies, governance mechanisms and objectives. While the extant literature has been focused on how VCs differ in their experience/reputation

[2] With regard to the former type of public support, examples are private/public partnerships in Israel (i.e., the Yozma program: for more details, see Avnimelech and Teubal, 2006); mutual funds in Canada (i.e., the Canadian Labour Sponsored Venture Capital Corporation – LSVCC: for more details, see Cumming and MacIntosh, 2007a, b) and the UK (Cumming, 2003); and limited partnerships in IVCs, in which the government invests alongside other private and institutional investors: e.g., the Australian Innovation Investment Funds (IIFs) (for more details, see Cumming, 2007 and Cumming and Johan, 2012), the Danish fund Vækstfonden, the Fund for the Promotion of Venture Capital in France, the German fund ERP-EIF Dachfonds, and the Dutch fund TechnoPartner Seed facility. With regard to public subsidies that are directed toward high-tech entrepreneurial firms, the main examples are grants (Lerner, 1999, 2002; Wallsten, 2000; Audretsch et al., 2002; Lach, 2002; Gans and Stern, 2003; Colombo et al., 2011, 2013) and tax credits (Hall and Van Reenen, 2000).

[3] This study adopts the prevailing criterion followed by the most known commercial datasets in the field (e.g., Thomson One) that classify the different types of VC funds according to the type of company through which funds are managed. In particular, here we focus on two basic different types of VC funds: funds managed by a company that is entirely possessed by governmental sources (GVCs) and the typical 'US style' independent venture capital funds (IVCs). It is worth noting that we do not have information on the financing sources of the VC funds. In this respect, note that governmental sources are unlikely to represent the major source of independent VC fundraising (see Mayer et al., 2005: p. 591). More importantly, GVCs predominantly invest public financial resources.

[4] We closely adhere to the two definitions that were provided by Tian (2012: pp. 249–250). In particular, our definition of syndication and co-financing refer to his first and second definition of syndication, respectively. It is worth noting that our analysis is not at the round level. Thus, we implicitly assume that IVCs and GVCs syndicate when they invest in the focal portfolio firm in the same year (see Brander et al., 2002 for the same criterion).

(e.g., Gompers, 1996; Nahata, 2008), networks (e.g., Hochberg et al., 2007), and in the design of contracts with their portfolio firms (e.g., Kaplan and Strömberg, 2003, 2004), relatively less is known about how the organizational structure and, in particular, the type of ownership of the VCs impacts on high-tech entrepreneurial firms' growth. According to a recent survey of Da Rin et al. (2011), this aspect is the most contended dimension of the differences among the VCs, and this heterogeneity is more pronounced in Europe than in the US. VC funds range from the archetypal US-style independent funds to bank-affiliated branches, passing through industrial subsidiaries and their corporate VC units, and governmental bodies. Those few studies that have tackled the issue have focused especially on a comparison between private operators, while leaving aside GVCs, especially due to lack of data.

With respect to GVCs and IVCs, their potential for having different impacts on the growth of high-tech entrepreneurial firms might be explained by several reasons. First, GVCs and IVCs have different objectives, although the latter might be directed toward the same goal: to foster the growth of their portfolio firms. As emphasized in Section 1, the growth of high-tech entrepreneurial firms is a priority from the EU policy perspective and is a consequent mission for EU GVCs. From a different 'objective function', the IVCs have two preferred exit routes: initial public offerings (IPOs) and acquisitions (i.e., trade-sales). Accordingly, IVCs push the growth of their portfolio firms to increase the likelihood of an IPO or to make them more attractive for trade-sale (Chemmanur et al., 2011). Second, IVCs and GVCs could differ in their 'value-added' activities and their consequent ability to reach their goal. If it is arduous on a priori ground to establish the direction of such differences, public officers are reputed to be less likely to match the quality level of consultancy services that specialized IVCs provide to portfolio firms (Leleux and Surlemont, 2003). Then, IVCs actively monitor portfolio firms (Lerner, 1995) through the use of specific financial instruments and contractual clauses (e.g., stage financing, allocation of control rights), which create high-powered incentives for entrepreneurs to pursue growth (Kaplan and Strömberg, 2003, 2004). Conversely, GVCs use fewer contract mechanisms for the active monitoring of portfolio firms as well as fewer voting rights than IVCs. An empirical comparison of the level and composition of value-added activities that are performed by GVCs and IVCs, as perceived by portfolio firms, is provided by Luukkonen et al. (2013). Using the VICO dataset, the authors show that IVCs are reputed to contribute more than GVCs in terms of the development of business ideas, managerial professionalization and exit orientation. Third, IVCs and GVCs might target different firms, according to their risk profile. For example, Mazzucato (2011) and Auerswald and Branscomb (2003) show that IVCs often appear to shy away from risky high-tech entrepreneurial firms (i.e., the financial returns are not high enough to justify the investment risk), and they prefer business ideas (and associated firms) that are already quite developed. Conversely, GVCs might show less risk-averse attitudes in their investment choices to the extent that they also value the social benefits that are brought in by the selected targets (see the discussion in Grilli and Murtinu, 2013). Finally, even though GVCs might not be inferior to IVCs in their screening processes (Lerner, 2002: p. 78), their investment decisions could be subjected to distortions and imperfections (e.g., 'pork barrel' spending).

### 2.3. Syndication and co-financing between IVCs and GVCs

There is a dearth of studies that focus on syndication and co-financing activities between different types of VCs from the perspective of portfolio firms. To the best of our knowledge, our work represents the first attempt to explicitly analyze the impact that co-investments between IVCs and GVCs exert on the growth of high-tech entrepreneurial firms.

In the extant literature, several reasons are advocated to justify syndication and co-financing. Syndicated and co-financed investments could be triggered by the willingness of VCs to (i) reduce information asymmetries in the screening process through a 'second opinion' (Lerner, 1994b); (ii) overcome capital constraints and exploit complementary resources, skills, networks and industry expertise of different VCs (Bygrave, 1987); (iii) diversify their investments and reduce overall portfolio risk (Lerner, 1994b); (iv) reduce agency problems with entrepreneurs (Admati and Pfleiderer, 1994); and (v) signal to the capital markets the quality of the focal VC syndicate-backed firm and influence the likelihood of a successful exit (Tian, 2012).

Usually, syndication between VCs is found to be beneficial for portfolio firms along a series of dimensions, which include growth. However, the extant literature lacks an appropriate evaluation of the effectiveness of 'mixed' syndicates, e.g., between IVCs and GVCs. In this respect, the intrinsic differences between IVCs and GVCs might exacerbate agency and transaction costs between the two types of investors in the syndicate (e.g., Wright and Lockett, 2003).

## 3. Data

### 3.1. The VICO dataset

This work draws on the VICO dataset. The VICO dataset is the result of a research project that is funded by the 7th Framework Programme of the European Commission (theme SSH-2007-1.2.3 – Grant Agreement 217485). A full description of the dataset is provided by Bertoni and Martí (2011). Below, we limit ourselves to describing its most relevant aspects.

The use of the VICO dataset has several advantages compared to other data sources. First, it solves an important problem that plagues some of the most popular datasets in the VC literature (e.g., the Thomson One database): the misreport of fund types outside of the US. For example, checks over Canadian and Australian data suggest that over 50% of the transactions registered by commercial sources could present problems of attribution to the wrong fund type (Cumming et al., 2013). Second, as testified by a recent report of the European Parliament (2012), the VICO database offers an extensive representation of the European population of VC-backed companies. This coverage allows us to overcome the very country-specific nature of the extant studies in the field that address the impact of GVC on entrepreneurial firms' growth performance (e.g., Beuselinck and Manigart, 2000 for Belgium; Balboa et al., 2007 for Spain). Third, the specific data collection process that was pursued to build up the VICO dataset enables a better coverage of investments that were made by non-independent VCs (including GVCs), especially in Europe, compared with the collections that are usually achieved by commercial databases (Ivanov and Xie, 2010: p. 135).

The VICO dataset includes data on high-tech entrepreneurial firms that operate in seven European countries (Belgium, Finland, France, Germany, Italy, Spain and the United Kingdom). The VICO dataset stores information on two groups of firms: VC-backed firms and non-VC-backed (but potentially targetable by VCs) firms, which were less than 20 years old in 2010 and, in addition, were created as independent entrepreneurial acts (i.e., not controlled by other business organizations) and are active in high-tech (manufacturing and services) industries (see Table 1). Both groups include surviving and non-surviving firms (i.e., firms that were acquired or liquidated).

For VC-backed firms, data were collected through a random extraction from several proprietary and commercial sources. Country-specific proprietary sources were 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

**Table 1**
Industry classification.

| Sector | NACE code(s) |
|---|---|
| Pharmaceutical | 24.4 |
| ICT manufacturing | 30.02 + 32 + 33 |
| TLC | 64.2 |
| Internet | 72.60 |
| Software | 72.2 |
| Biotech | 73.1 |
| Other | – |

The residual industry 'Other' includes Robotics (NACE: 29.5), Aerospace (NACE: 35.5), and other industries that are not explicitly included in the NACE classification: Energy and Nanotech.

(Spain), the Library House (now Venture Source, UK), press releases and press clippings, and initial public offering (IPO) prospectuses. Commercial databases were the Thomson One database, VCPro-Database, and Zephyr. A central data collection unit ensured that the information was consistent and comparable across countries. In particular, data were cross-checked with those data sources that were available from public sources, e.g., reports provided by the national associations of private equity investors and the websites and financial reports of the VCs. The number of VC-backed firms was restricted to those that received their first investment round before the tenth year after the foundation. Because of the data limitations in the years before the early 1990s and the necessity of a minimum number of post-investment observations to evaluate the impact of VCs on portfolio firm performances, the VICO dataset includes VC-backed firms that received their first investment round between 1994 and 2004. The VICO dataset includes equity (or equity-like) financing that was provided by VCs to entrepreneurial firms (i.e., seed, early-stage, late-stage and expansion capital), while information on LBOs, real estate, distressed debt funds and other private equity investments are not included.

For the identification of non-VC-backed firms, we resort to a random extraction from proprietary and commercial databases. The main commercial source was Amadeus. All of the available vintage years of Amadeus were used to build a population such that non-surviving firms were included. Country-specific proprietary

**Table 3**
Co-financing and syndication between GVC and IVC investors.

| | GVC | | | | | |
|---|---|---|---|---|---|---|
| | Before | | Syndicated | | After | |
| | N. firms | % | N. firms | % | N. firms | % |
| IVC | 23 | 18.25 | 65 | 51.59 | 38 | 30.16 |

Numbers in the cells refer to the total number of co-financed firms reported in Table 2.

sources were also used to improve the coverage of the dataset (e.g., Credit reform in Germany, Italian business community's data bank in Italy). To summarize, the VICO dataset consists of 8370 firms, 759 of which are VC backed (data accessed on December 19th 2011).

### 3.2. Descriptive statistics

The number of IVC- and GVC-backed firms is 538 and 239, respectively. Among them, 126 firms received VC from both types of investors. Table 2 reports the number and ratio of IVC-backed and GVC-backed firms and the subset of co-financed firms across countries and industries. Among the IVC-backed firms, the UK represents the most developed VC market (27.32% of the total IVC-backed firms), followed by Germany (18.59%) and France (18.22%). The situation is different for the GVC-backed firms, where France has the greatest share (20.08%), followed by Spain (17.99%) and Germany (15.06%). France is also the leading country in terms of co-financed investments between IVCs and GVCs (31.75%), followed by the UK (15.87%) and Germany (14.29%). Among the industries that were investigated herein, software represents the main target for both IVCs (40.52%) and GVCs (38.08%). ICT manufacturing (18.03%) and biotechnology (24.69%) represent the second largest target market for IVCs and GVCs, respectively. Co-finance activity is not numerically negligible. Co-financed investments are mainly targeted to software and biotechnology industries (41.27% and 24.60%, respectively).

Table 3 presents statistics about the temporal dynamics of co-financing and syndication between GVCs and IVCs. In more than a

**Table 2**
IVC- and GVC-backed firms across countries and industries.

| | IVC-backed firms | | GVC-backed firms | | Co-financed firms | |
|---|---|---|---|---|---|---|
| | N. firms | % | N. firms | % | N. firms | % |
| **Country** | | | | | | |
| Belgium | 58 | 10.78 | 33 | 13.81 | 16 | 12.70 |
| Finland | 50 | 9.29 | 34 | 14.23 | 16 | 12.70 |
| France | 98 | 18.22 | 48 | 20.08 | 40 | 31.75 |
| Germany | 100 | 18.59 | 36 | 15.06 | 18 | 14.29 |
| Italy | 48 | 8.92 | 18 | 7.53 | 6 | 4.76 |
| Spain | 37 | 6.88 | 43 | 17.99 | 10 | 7.94 |
| United Kingdom | 147 | 27.32 | 27 | 11.30 | 20 | 15.87 |
| **Total** | **538** | **100.00** | **239** | **100.00** | **126** | **100.00** |
| **Industry** | | | | | | |
| Pharmaceutical | 20 | 3.72 | 5 | 2.09 | 2 | 1.59 |
| ICT manufacturing | 97 | 18.03 | 44 | 18.41 | 27 | 21.43 |
| TLC | 32 | 5.95 | 9 | 3.77 | 4 | 3.17 |
| Internet | 67 | 12.45 | 13 | 5.44 | 6 | 4.76 |
| Software | 218 | 40.52 | 91 | 38.08 | 52 | 41.27 |
| Biotech | 87 | 16.17 | 59 | 24.69 | 31 | 24.60 |
| Other | 17 | 3.16 | 18 | 7.53 | 4 | 3.17 |
| **Total** | **538** | **100.00** | **239** | **100.00** | **126** | **100.00** |

The sample includes VC-backed firms that enter the VICO dataset between 1984 and 2004 that first receive VC funding in the year that they enter the VICO dataset or in any subsequent year. Columns I, III and V show the number of IVC-backed firms, GVC-backed firms and co-financed firms, according to country and industry, respectively. Columns II, IV and VI show the percentage of IVC-backed firms (calculated with respect to the total number of IVC-backed firms), the percentage of GVC-backed firms (calculated with respect to the total number of GVC-backed firms), and the percentage of co-financed firms (calculated with respect to the total number of co-financed firms), according to country and industry, respectively.

**Table 4**
Descriptive statistics.

| Column | IVC-backed firms | | GVC-backed firms | | Co-financed firms | | Non VC-backed firms | |
|---|---|---|---|---|---|---|---|---|
| | I Mean | II Std. Dev. | III Mean | IV Std. Dev. | V Mean | VI Std. Dev. | VII Mean | VIII Std. Dev. |
| Sales (k€) | 6001.074 | 25,248.260 | 3199.835 | 7369.103 | 3507.801 | 8535.808 | 6514.444 | 67,567.070 |
| Employees | 34.051 | 60.016 | 26.516 | 44.442 | 29.003 | 40.805 | 40.791 | 305.643 |
| Age | 5.857 | 4.215 | 6.194 | 4.466 | 5.903 | 4.205 | 6.896 | 5.066 |

Statistics based on the VICO dataset. In columns I, III, V and VII, the mean value of the focal variable related to IVC-backed firms, GVC-backed firms, co-financed firms and non-VC-backed firms, respectively. In columns II, IV, VI and VIII, the standard deviation of the focal variable related to IVC-backed firms, GVC-backed firms, co-financed firms and non-VC-backed firms, respectively. Mean and standard deviation values calculated on all firms included in a category in all years of operation, both before and after the eventual receipt of VC funding. Deflated sales values are expressed in k€.

half of the co-financed investments (51.59%), there is syndication between IVCs and GVCs.

In Table 4, we report some descriptive statistics about the size (both in terms of the sales value and the number of employees) and the age for VC-backed and non-VC-backed firms that are included in the VICO dataset. IVC-backed firms are, on average, larger than both GVC-backed and co-financed firms but (slightly) smaller than non-VC-backed firms, both in terms of the sales value (on average c.a. €6 million for IVC-backed firms vs. c.a. €3 million for GVC-backed, €3.5 million for co-financed and €6.5 million for non VC-backed firms) and headcount (on average c.a. 34 employees for IVC-backed firms vs. c.a. 26 employees for GVC-backed, 29 employees for co-financed and 41 employees for non VC-backed firms). Age distributions are comparable across all categories (approximately 6 years old).

## 4. Econometric framework

### 4.1. Matching procedure

To appropriately evaluate the average impact that is exerted by different types of VCs on high-tech entrepreneurial firm growth, we define three different types of 'treated' firms: (1) the IVC-backed firms (which potentially received a GVC investment after the initial IVC round); (2) the GVC-backed firms (which potentially received an IVC investment after the initial GVC round); and (3) the VC syndicate-backed firms, which receive an initial syndicated investment by GVCs and IVCs.

For each of these three 'states of nature', we use a propensity score method to match each VC-backed firm to a similar non-VC-backed firm (see Görg and Strobl, 2007, for an identical approach in a different context). Matching procedures are well established in the VC literature (e.g., Megginson and Weiss, 1991; Puri and Zarutskie, 2012; Chemmanur et al., 2011; Tian, 2012; Croce et al., 2013b). In fact, VC financing can hardly be considered to be the result of a random process: entrepreneurial firms choose whether to search for VC funding, and VCs accurately select their portfolio firms. Specifically, we built a matched sample of non-VC-backed firms that were comparable to the sample of VC-backed firms in each of the three categories reported above, according to a set of a priori characteristics.[5] For each category of VC-backed firms that received the first VC financing in the year $t$, we performed a one-to-one matching without replacement in the year $t$. Propensity scores were obtained through a logit model on a set of independent variables: the firm age, firm size, country and industry controls. We use a model specification that has covariates that are identical to those used in Puri and Zarutskie (2012), with the only obvious exception being that we have European countries (and not US regions) as geographical controls. As industry controls, we refer to the industries that are shown in Table 1. All of the details on the matching procedure(s) and balancing tests that we performed are provided in Appendix A. The three matched samples are labeled 'IVC vs. no VC financing', 'GVC vs. no VC financing' and 'Syndication vs. no VC financing', respectively.

### 4.2. Model specification

The impact of GVC and IVC investments on firm growth is investigated through the estimation of a series of augmented Gibrat law panel data models (Evans, 1987) that are derived from the following model specification:

$$LnGrowth_{i,t} = \alpha_0 + \alpha_1 LnSize_{i,t-1} + \alpha_2 LnAge_{i,t} + \psi' VC_{i,t-1} + C_i + S_i + T_i + W_i + \varepsilon_{i,t}. \quad (1)$$

This equation is a standard specification in the industrial organization literature on firm growth (e.g., Sutton, 1997; Caves, 1998), which allows us to test whether the growth rates of VC-backed firms persistently increase after the first round of IVC or GVC (or an initial IVC-GVC syndicated investment) with respect to non-VC-backed firms. $LnGrowth_{i,t}$ is the natural logarithmic firm growth between time $t-1$ and $t$ (i.e., $LnSize_{i,t} - LnSize_{i,t-1}$); $LnSize_{i,t-1}$ is the logarithm of the firm size at time $t-1$ (the argument was augmented by 1 in the case of a value of 0); $VC_{i,t-1}$ is a vector of step dummy variables that indicate the VC status of firms (i.e., the variables switch permanently from 0 to 1 in the year following the first VC round)[6]; $C_i$ and $S_i$ are country and industry dummies, respectively; $T_i$ are year dummies that capture time-varying macroeconomic shocks; $W_i$ are unobservable firm-specific factors; and $\varepsilon_{i,t}$ are i.i.d. error terms.[7] We measure the firm size as the number of employees and the sales value (deflated by using the consumer price index, with the year 2005 the reference year;

[5] Before performing propensity score matching (PSM), we remove from the dataset: (i) firms that are included in the industry Other (see Table 1) because of the excessive heterogeneity of the industries included; (ii) firms that are backed by bank-affiliated VCs, corporate VCs, university-sponsored VCs; and (iii) firms that are backed by VCs that have a missing name, address and/or contact information in the VICO dataset. We excluded VC-backed firms in categories (ii) and (iii) from the year of VC funding onward and not before because they could represent a potential target for IVCs and GVCs in that period. However, as a robustness check, we exclude from the dataset VC-backed firms in categories (ii) and (iii) also in the years before VC funding, and we re-estimate our model(s), which are presented in Section 5. The results are quite unchanged and are available upon request from the authors.

[6] Variables are lagged as a very preliminary estimation strategy to reduce the potential reverse causality concerns. Note that these variables do not switch back to 0 when the VC investors exit. The reason is that VC-backed firms are inherently different from non-VC-backed firms. For example, VC financing is assumed to signal the quality of a firm to uninformed third parties, making it easier for the firm to obtain access to additional resources independently of the presence of a VC investor in the firm (Megginson and Weiss, 1991; Hsu, 2004; Croce et al., 2013a).

[7] This approach is analogous to the dynamic specification for the test of the Gibrat law that was suggested by Chesher (1979). In other words, starting from a dynamic equation $LnSize_{i,t} = \alpha_0 + \beta LnSize_{i,t-1} + \alpha_2 LnAge_{i,t} + \psi' VC_{i,t-1} + C_i + S_i + T_i + W_i + \varepsilon_{i,t}$ and subtracting from both members $LnSize_{i,t-1}$, one obtains Eq. (1) with $\alpha_1$ equal to $(\beta - 1)$.

source: Eurostat), alternatively. The availability of employment and sales data defines our observation period in the time frame from 1993 (or the year of the firm's foundation) to 2010 (or the year of the firm's exit from the dataset).

Overall, the three matched samples 'IVC vs. no VC financing', 'GVC vs. no VC financing' and 'Syndication vs. no VC financing' include 6.59 (6.94), 7.74 (7.84) and 6.73 (7.09) yearly observations per firm in the sales (employees) growth specification, respectively.

## 5. Results

### 5.1. The impact of IVC and GVC investments on firm growth

Table 5 presents the estimates of the two basic model specifications of Eq. (1). In Panel A, $VC_{i,t-1}$ is constituted by $IVC_{i,t-1}$, and regressions are run on the 'IVC vs. no VC financing' sample. In Panel B, $VC_{i,t-1}$ is constituted by $GVC_{i,t-1}$, and regressions are run on the 'GVC vs. no VC financing' sample.

Columns (I) to (IV) refer to sales growth, while columns (V) to (VIII) refer to employee growth. Different panel estimators are used. Pooled OLS estimates that control for country, industry and time dummies are shown in columns (I) and (V). The estimates highlight a positive and significant impact of IVC on both the sales and the employee growth. Conversely, the impact of GVC is of much lesser magnitude than IVC and is never statistically significant.

In columns (II) and (VI), we turn to a fixed effects (FE) estimation, which removes any potential concerns on the endogeneity of independent variables due to their alleged correlation with $W_i$.[8] Interestingly, the positive and significant impact of IVC is confirmed in the sales growth equation, while it loses statistical significance (even though it is still positive) in the employee growth regression. More specifically, becoming an IVC-backed firm results in a short-run increase in the yearly sales growth of +38.3% (which is significant at 1%). With respect to GVC, the results are in line with OLS estimates in the sales growth equation. Conversely, they show a negative (although not significant) coefficient in the employee equation.

In principle, if VCs observe a set of firm-specific time-varying characteristics that we are not able to control for, and these latter characteristics influence positively (or negatively) both the VCs' decision to invest and the growth performance of their portfolio firms, the impact of $IVC_{i,t-1}$ and $GVC_{i,t-1}$ on the firm growth estimated through OLS and FE would be biased. Thus, to complement the FE estimation and account for the possible biases that are caused by both the dynamic specification[9] and the unobserved *time-varying* heterogeneity, we resort to the two-step system generalized method of moments (GMM-SYS) approach (Blundell and Bond, 1998). We do not consider GMM-SYS to be strictly valid per se, but we deem it to be a robustness check (among the others that we perform; see Section 6.2) in that the results that are obtained through the FE estimator were not simply driven by some omitted *time-varying* unobserved variables (for a similar use of the GMM-SYS approach, see, e.g., Stoyanov, 2011; and for applications in the VC literature, see, e.g., Samila and Sorenson, 2011).[10] In particular, we make the conservative assumption that the VC variables and the lagged size measure are potentially endogenous, and we run two different GMM-SYS estimators. The first estimator (columns III and VII) uses a reduced instrument set, with moment conditions in the interval of $t-3$ ($t-2$) to $t-4$ ($t-3$) for instruments in levels (differences).[11] The use of this specific time-lag structure is justified by the fact that the use of a large number of instruments potentially results in a significant finite-sample bias (Roodman, 2009) and measurement errors could cause potential distortions (Bond, 2002). The second GMM-SYS estimator (columns IV and VIII) uses all of the available moment conditions of the time series but collapses the instruments set as suggested by Roodman (2009: pp. 148–149). Note that in all of the GMM regressions, we applied the finite-sample correction for the two-step covariance matrix that was suggested by Windmeijer (2005).[12] Tests on the reliability of the instruments in the levels and differences are provided in Appendix B.

The GMM-SYS results are substantially in line with those highlighted by the FE estimator and reveal that a truly positive and statistically significant impact is exerted only by the IVCs on the sales growth. The magnitude of this effect is somehow reduced by the GMM-SYS estimators but is still important in both economic and statistical terms, ranging from +19.5% (significant at 5%) to +33% (significant at 1%).[13] The coefficient of the variable $GVC_{i,t-1}$ is always found to be not statistically significant in the GMM-SYS estimates (except for a negative sign that is significant at 5% in column VII of Panel B). Note, however, that in this case (as in all GMM-SYS estimates of the employee growth equation in Table 5), the coefficient of $LnSize_{i,t-1}$ is not significantly different from zero. This coefficient corresponds to the coefficient of the lagged size variable in Chesher's dynamic specification (see footnote 7) being not different from one, which makes the whole GMM approach highly unreliable.

Finally, let us briefly consider the estimated effects of the firm size and age on the growth rates. The coefficient for the firm size is always negative and is prevalently significant at the conventional confidence levels. Similarly, the estimated coefficient for the firm's age, when statistically significant, has a negative sign. Both of the results are consistent with the prevailing (but not unanimous) evidence that is highlighted by the empirical literature on the Gibrat

[8] As suggested by Wooldridge (2002), the FE estimator is usually more efficient than first-differences OLS. Moreover, in our context of analysis, first-differences OLS is a 'too short memory' estimator (Laporte and Windmeijer, 2005).

[9] We also compute the bias-corrected least-squares dummy variable (LSDV) estimator for standard autoregressive panel data models, using the bias approximation suggested by Bruno (2005). The dynamic bias in the FE estimates is decreasing in $T$ (e.g., Bond, 2002). Thus, the dynamic bias should be limited in our analysis because our time frame is sufficiently long. In fact, results of the bias corrected-LSDV estimates as to the coefficients of both $LnSize_{i,t-1}$ and the dummy variables of interest always appear to be quite similar to those that are estimated through the FE method. A series of Hausman tests (whose results are available upon request from the authors) do not reject the null hypothesis of the equality of the coefficients between FE and bias corrected-LSDV estimators.

[10] Other instrumental variables (IV) methods are less compelling in our context due to the pitfalls in controlling for the dynamic bias in our model specification. Moreover, it is difficult to find valid and reliable external firm-specific instruments for the vector $VC_{i,t-1}$. For more details, see Appendix B.

[11] In our GMM-SYS estimates, the ratio between the number of instruments and the number of groups is always far below 1. The ratio between the number of instruments and the number of observations is always extremely low in the first two samples – 'IVC vs. no VC financing' and 'GVC vs. no VC financing' – (ranging from 0.0101 to 0.0434 and from 0.0290 to 0.1077, respectively), while it sensibly increases in the third matched sample – 'Syndication vs. no VC financing'. It is worth noting that in the latter case, the Hansen statistics assume the implausibly perfect $p$-value of 1.000. In this case, the GMM-SYS results are not reliable and, accordingly, are not presented (see Table 7).

[12] We also employ small-sample formulas for estimating the covariance matrix and the corresponding standard errors. The results are almost unchanged and are available upon request from the authors.

[13] As highly emphasized in the econometric literature (Bond, 2002), the FE estimator produces, by construction, an upward bias in the absolute value of the coefficient $\alpha_1$ in Eq. (1), corresponding to a downward bias in the estimate of $\beta$ in the Chesher's specification (see footnote 7). Unavoidably, this leads the FE method to overstate the VC short-run effects herein reported, and understate the long-run effects that will be presented in Section 6.1.2 (see Eq. (2)). The misleading influence of the dynamic bias in FE estimates is very limited in our case (see footnote 9). However, for the sake of prudence, FE results have to be regarded as extreme bounds of the real impact of the variables of interest on firm growth.

**Table 5**
The impact of IVC and GVC investments on European high-tech entrepreneurial firms' growth.

| | Sales growth | | | | Employee growth | | | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | GMM-SYS ($t-3$; $t-4$) | GMM-SYS (collapse: $t-3$; earlier) | OLS | FE | GMM-SYS ($t-3$; $t-4$) | GMM-SYS (collapse $t-3$; earlier) |
| Column | I | II | III | IV | V | VI | VII | VIII |
| **Panel A: IVC vs. no VC financing** | | | | | | | | |
| LnSize ($t-1$) | −0.1521*** (0.0213) | −0.6379*** (0.0466) | −0.2599*** (0.0716) | −0.2710*** (0.0655) | −0.0539*** (0.0129) | −0.4219*** (0.0485) | −0.0551 (0.0379) | −0.0273 (0.0477) |
| LnAge ($t$) | −0.2256*** (0.0507) | 0.1051 (0.1774) | −0.1520 (0.1037) | −0.1335 (0.1148) | −0.1346*** (0.0205) | −0.0755 (0.0869) | −0.1230*** (0.0340) | −0.1308*** (0.0385) |
| IVC ($t-1$) | 0.2159*** (0.0526) | 0.3830*** (0.1186) | 0.1948** (0.0891) | 0.3298*** (0.1160) | 0.1009*** (0.0263) | 0.0934 (0.0762) | −0.0129 (0.0592) | −0.0438 (0.0710) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country dummies | Yes | – | Yes | Yes | Yes | – | Yes | Yes |
| Industry dummies | Yes | – | Yes | Yes | Yes | – | Yes | Yes |
| Obs. | 2143 | 2143 | 2143 | 2143 | 2375 | 2375 | 2375 | 2375 |
| Groups | 325 | 325 | 325 | 325 | 342 | 342 | 342 | 342 |
| $R^2$ | 0.1879 | 0.1187 | – | – | 0.1235 | 0.0378 | – | – |
| AR (1) | – | – | −3.96*** | −3.90*** | – | – | −2.39** | −3.07*** |
| AR (2) | – | – | 0.06 | 0.03 | – | – | 0.05 | 0.03 |
| Hansen test ($p$-value) | – | – | 78.26 [76] (0.407) | 30.81 [25] (0.195) | – | – | 81.96 [74] (0.246) | 67.92 [24] (0.000) |
| **Panel B: GVC vs. no VC financing** | | | | | | | | |
| LnSize ($t-1$) | −0.1301*** (0.0316) | −0.5001*** (0.0599) | −0.2155** (0.1058) | −0.3594*** (0.1145) | −0.0478*** (0.0169) | −0.3573*** (0.0330) | −0.0524 (0.0385) | −0.1126 (0.0724) |
| LnAge ($t$) | −0.2219** (0.0946) | 0.0456 (0.2834) | 0.0157 (0.2206) | 0.1429 (0.2573) | −0.1306*** (0.0345) | −0.1183 (0.1159) | −0.1258*** (0.0473) | −0.0940* (0.0492) |
| GVC ($t-1$) | 0.0653 (0.0687) | 0.0513 (0.1480) | −0.0203 (0.1273) | 0.0474 (0.1554) | 0.0321 (0.0320) | −0.1034 (0.1051) | −0.1381** (0.0686) | −0.0805 (0.0596) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country dummies | Yes | – | Yes | Yes | Yes | – | Yes | Yes |
| Industry dummies | Yes | – | Yes | Yes | Yes | – | Yes | Yes |
| Obs. | 882 | 882 | 882 | 882 | 964 | 964 | 964 | 964 |
| Groups | 114 | 114 | 114 | 114 | 123 | 123 | 123 | 123 |
| $R^2$ | 0.1854 | 0.0971 | – | – | 0.1100 | 0.0285 | – | – |
| AR (1) | – | – | −2.08** | −1.92* | – | – | −4.75*** | −4.21*** |
| AR (2) | – | – | −0.19 | −0.22 | – | – | 0.11 | 0.21 |
| Hansen test ($p$-value) | – | – | 68.92 [77] (0.733) | 25.50 [27] (0.546) | – | – | 81.02 [76] (0.326) | 25.65 [28] (0.592) |

The dependent variables are the sales growth (columns I–IV) and the employee growth (columns V–VIII). Country, industry and time dummies are included in the estimates (the coefficients are omitted in the table). The estimates are derived from OLS regressions with standard errors that are robust to heteroskedasticity through the Huber-White method and serial correlation within firms (columns I and V), FE regressions with robust standard errors (columns II and VI), GMM-SYS with moment conditions of endogenous variables restricted to the interval $t-3$ ($t-2$) and $t-4$ ($t-3$) for instruments in levels (differences) with finite-sample correction for the two-step covariance matrix developed by Windmeijer (2005) (columns III and VII) and GMM-SYS with 'collapsed' instruments with finite-sample correction for the two-step covariance matrix developed by Windmeijer (2005) (columns IV and VIII). All of the regressions are estimated with an intercept term. Standard errors and $p$-values of Hansen statistics are in round brackets. Degrees of freedom are in square brackets.

* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$.

law, which is that smaller and younger firms tend to grow faster than larger and more mature firms (e.g., Evans, 1987).

### 5.2. The impact of co-financing on the firm growth

To gain further insights and enrich our understanding of the phenomenon, in Table 6 we explore whether any differences arise in the VC impact due to co-financing between GVCs and IVCs. In Panel A, the vector $VC_{i,t-1}$ includes $IVC_{i,t-1}$, and the step dummy variable $GVCafter_{i,t-1}$, which captures a possible subsequent GVC investment after the IVC investment. In Panel B, in the same way, $VC_{i,t-1}$ includes $GVC_{i,t-1}$, and the step dummy variable $IVCafter_{i,t-1}$.

We employ the same set of estimators as in the previous analysis. In the sample 'IVC vs. no VC financing' (Panel A), the impact of IVC on the sales growth continues to remain positive and strongly significant (regardless of the estimation technique that is employed), and the magnitude of the effect is only marginally affected by the addition of the GVC variable. Conversely, $GVCafter_{i,t-1}$ exerts a positive and significant effect in the OLS (+19.8% significant at 10%) and FE regressions (+83.4% significant at 5%), but this effect is strongly reduced in both the magnitude and statistical significance in the GMM-SYS estimates.

With respect to the employment growth, the IVC variable is not statistically significant in all of the performed regressions (with the exception of OLS, as in Table 5). $GVCafter_{i,t-1}$ is positive but is not statistically significant in the FE estimates, while it increases in magnitude and statistical significance in the GMM-SYS estimates. However, this latter result is again far from being reliable (the coefficient of the lagged size variable is not significantly different from 0 in column VII), and we consider it to be imprudent to draw a conclusion about a positive moderating role of GVC on the employee growth of the IVC-backed firms.

Turning to the sample 'GVC vs. no VC financing' (Panel B), the role of co-financing appears to mirror the role highlighted above. Again, the positive impact of $IVCafter_{i,t-1}$ on the sales growth in the FE estimates (+43.4%, significant at 10% only) is not confirmed by the GMM analysis. In the same way, the positive and significant sign of the variable $IVCafter_{i,t-1}$ on employee growth highlighted by GMM-SYS estimates appears to be driven more by (ineludible) concerns in the GMM methodology rather than representing a truly genuine positive impact.

### 5.3. The impact of syndication on firm growth

In Table 7, we focus on the sample 'Syndication vs. no VC financing' and investigate the effects of syndicated investments by IVCs and GVCs on the growth of high-tech entrepreneurial firms. In Panel A, $VC_{i,t-1}$ is composed by a single step dummy variable ($VCSyndicate_{i,t-1}$), which captures entrepreneurial firms that receive their first VC investment by IVCs and GVCs in the same year. In Panel B, we also distinguish whether the leader of the syndicate is a GVC or an IVC investor ($GVCLeader_{i,t-1}$ or $IVCLeader_{i,t-1}$, respectively). Within the syndicate, the lead investor provides more financial resources and adds more value to the portfolio firm than other VCs (Wright and Lockett, 2003). The VICO dataset identifies the lead investor in a syndicated investment on the basis of secondary information sources and/or data on the distribution of the amount invested and the equity stakes possessed by syndicated partners.

In this case, we show only OLS and FE estimates because the conditions for performing GMM are a priori difficult to meet. In fact, the number of instruments is always higher than the number of firms. Panel A reveals that the syndication between the GVCs and IVCs does not exert any statistically significant effect on the VC syndicate-backed firms' growth. This null impact applies to both the sales and employee growth. In this latter case, the positive and statistically significant coefficient at 10% of $VCSyndicate_{i,t-1}$ in the OLS estimates is found to lose statistical significance in the FE regression.

Further insights can be gained by distinguishing syndicates that are led by a GVC investor from those that are led by an IVC investor. Consistent with all of the exposed findings and in particular with the results presented in Table 5 (Panel A), the only positive and statistically significant impact of syndication on entrepreneurial firm growth is exerted when (i) the sales growth measure is used, and (ii) the GVCs do not appear as the leaders of the syndicate. Although the robustness of these results cannot be tested through the GMM estimator(s), they confirm the benefit in terms of the sales growth of being VC-backed by a specialized independent investor (+59.9% significant at a 10% confidence level). At the same time, they further suggest the negligible 'direct' role of GVCs in spurring the portfolio firm growth as measured by the sales value and employees.

## 6. Additional evidence and further robustness checks

The findings that were reported in Section 5 have been further investigated and checked.

### 6.1. Additional evidence

#### 6.1.1. Value-added and financial effects

In Section 5, the entire set of estimates shows that IVCs spur the sales growth of high-tech entrepreneurial firms, either alone or as leaders in syndicated investments with GVCs. Conversely, the impact of GVCs is negligible. With regard to these main results, we ask: 'is it the higher growth performance of IVC-backed (IVC-led syndicate-backed) firms due to the sole injection of capital or is it also due to a value-added function that is performed by the IVCs (the syndicates led by the IVCs)?'. To explore this issue, in Table 8, we re-estimate the sales growth regressions that are shown in Table 5 (columns II and IV) and Table 7 (Panel B, column II), inserting the logarithm of the total VC amount that was (potentially) provided by IVCs and GVCs in the year $t-1$ (Panel A) or the logarithm of the cumulated VC amount that was (potentially) provided by IVCs and GVCs in the years $t-1$, $t-2$ and $t-3$ (Panel B).[14] With regard to the sample 'IVC vs. no VC financing' (columns I and II), the results in Panel A are fully in line with those highlighted in Section 5.1 and reveal a positive and significant (at 1%) coefficient for $IVC_{i,t-1}$ for the yearly sales growth (ranging from +30.6% to +39.6%). The coefficient of the total VC amount that was received in the year $t-1$ ($VC\,Amount_{i,t-1}$) does not turn out to be significantly different from zero, which suggests that the IVCs provide more than mere financial resources and points to the value-added function that is performed by these investors. Similar results are obtained when inserting the cumulated VC amount that was received in the years $t-1$, $t-2$ and $t-3$ (Panel B): the coefficient of the total VC amount that was received ($VC\ Amount_{i,t-1;t-3}$) is not statistically significant, and the magnitude of the coefficient that is related to IVC is weakly affected by its inclusion. Additionally, the results on the sample 'GVC vs. no VC financing' (columns III and IV) are fully comparable with those highlighted in Section 5.1 and confirm that there is a negligible impact of the GVCs on the sales growth of their portfolio firms. Turning to the sample 'Syndication vs. no VC financing' (column V), the results in Panel A show that the magnitude of the impact of the dummy $Syndicate\ IVC\ Leader_{i,t-1}$ on the firm sales growth is lower but is comparable to the magnitude shown in Section 5.3 (+52.7% vs. +59.9%), and its effect is now only close to significance. Interestingly, when we look at the results in Panel B,

[14] The argument of the logarithm was augmented by 1.

**Table 6**
The impact of VC investments on European high-tech entrepreneurial firms' growth: the role of co-financing.

| | Sales growth | | | | Employee growth | | | |
|---|---|---|---|---|---|---|---|---|
| | OLS | FE | GMM-SYS ($t-3$; $t-4$) | GMM-SYS (collapse: $t-3$; earlier) | OLS | FE | GMM-SYS ($t-3$; $t-4$) | GMM-SYS (collapse $t-3$; earlier) |
| Column | I | II | III | IV | V | VI | VII | VIII |
| **Panel A: IVC vs. no VC financing** | | | | | | | | |
| LnSize ($t-1$) | −0.1524$^{***}$ (0.0213) | −0.6401$^{***}$ (0.0463) | −0.2992$^{***}$ (0.0692) | −0.3171$^{***}$ (0.0616) | −0.0538$^{***}$ (0.0129) | −0.4225$^{***}$ (0.0485) | −0.0579 (0.0390) | −0.1122$^{**}$ (0.0465) |
| LnAge ($t$) | −0.2265$^{***}$ (0.0509) | 0.0875 (0.1748) | −0.0983 (0.1222) | −0.0745 (0.1120) | −0.1344$^{***}$ (0.0206) | −0.0782 (0.0871) | −0.1361$^{***}$ (0.0337) | −0.0895$^{**}$ (0.0422) |
| IVC ($t-1$) | 0.2027$^{***}$ (0.0545) | 0.3724$^{***}$ (0.1183) | 0.2464$^{**}$ (0.0993) | 0.3458$^{***}$ (0.1134) | 0.1027$^{***}$ (0.0271) | 0.0913 (0.0764) | −0.0290 (0.0643) | 0.0339 (0.0640) |
| GVCafter ($t-1$) | 0.1980$^{*}$ (0.1021) | 0.8337$^{**}$ (0.3232) | 0.0474 (0.2506) | 0.1473 (0.1431) | −0.0286 (0.0387) | 0.0828 (0.0585) | 0.1199$^{**}$ (0.0526) | 0.1151$^{*}$ (0.0609) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country dummies | Yes | – | Yes | Yes | Yes | – | Yes | Yes |
| Industry dummies | Yes | – | Yes | Yes | Yes | – | Yes | Yes |
| Obs. | 2143 | 2143 | 2143 | 2143 | 2375 | 2375 | 2375 | 2375 |
| Groups | 325 | 325 | 325 | 325 | 342 | 342 | 342 | 342 |
| $R^2$ | 0.1887 | 0. 1194 | – | – | 0.1236 | 0.0378 | – | – |
| AR (1) | – | – | −3.90$^{***}$ | −3.92$^{***}$ | – | – | −2.70$^{***}$ | −3.03$^{***}$ |
| AR (2) | – | – | 0.08 | 0.03 | – | – | 0.05 | 0.04 |
| Hansen test ($p$-value) | – | – | 91.69 [93] (0.519) | 37.40 [34] (0.316) | – | – | 89.12 [91] (0.536) | 26.72 [33] (0.772) |
| **Panel B: GVC vs. no VC financing** | | | | | | | | |
| LnSize ($t-1$) | −0.1301$^{***}$ (0.0316) | −0.5054$^{***}$ (0.0594) | −0.2180$^{**}$ (0.1034) | −0.3806$^{***}$ (0.1284) | −0.0497$^{***}$ (0.0172) | −0.3584$^{***}$ (0.0321) | −0.0812 (0.0493) | −0.1352$^{*}$ (0.0724) |
| LnAge ($t$) | −0.2274$^{**}$ (0.0970) | 0.0387 (0.2808) | −0.0105 (0.2095) | 0.1655 (0.3010) | −0.1363$^{***}$ (0.0343) | −0.1209 (0.1150) | −0.1249$^{**}$ (0.0518) | −0.1001$^{**}$ (0.0471) |
| GVC ($t-1$) | 0.0567 (0.0735) | 0.0400 (0.1497) | −0.0204 (0.1263) | 0.0948 (0.1711) | 0.0232 (0.0318) | −0.1059 (0.1027) | −0.1187$^{*}$ (0.0669) | −0.0812 (0.0586) |
| IVCafter ($t-1$) | 0.0883 (0.0970) | 0.4343$^{*}$ (0.2434) | 0.2059 (0.1817) | 0.2086 (0.2236) | 0.1218 (0.0859) | 0.0771 (0.2025) | 0.3052$^{*}$ (0.1830) | 0.2597$^{**}$ (0.1271) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country dummies | Yes | – | Yes | Yes | Yes | – | Yes | Yes |
| Industry dummies | Yes | – | Yes | Yes | Yes | – | Yes | Yes |
| Obs. | 882 | 882 | 882 | 882 | 964 | 964 | 964 | 964 |
| Groups | 114 | 114 | 114 | 114 | 123 | 123 | 123 | 123 |
| $R^2$ | 0.1858 | 0.0974 | – | – | 0.1132 | 0.0290 | – | – |
| AR (1) | – | – | −2.09$^{**}$ | −1.87$^{*}$ | – | – | −4.71$^{***}$ | −4.24$^{***}$ |
| AR (2) | – | – | −0.20 | −0.25 | – | – | 0.00 | 0.12 |
| Hansen test ($p$-value) | – | – | 73.24 [95] (0.952) | 34.95 [34] (0.423) | – | – | 82.44 [94] (0.797) | 29.02 [35] (0.751) |

The dependent variables are sales growth (columns I–IV) and employee growth (columns V–VIII). Country, industry and time dummies are included in the estimates (the coefficients are omitted in the table). The estimates are derived from OLS regressions with standard errors that are robust to heteroskedasticity through the Huber-White method and serial correlation within firms (columns I and V), FE regressions with robust standard errors (columns II and VI), GMM-SYS with moment conditions of endogenous variables restricted to the interval $t-3$ ($t-2$) and $t-4$ ($t-3$) for instruments in levels (differences) with finite-sample correction for the two-step covariance matrix developed by Windmeijer (2005) (columns III and VII), and GMM-SYS with 'collapsed' instruments with finite-sample correction for the two-step covariance matrix developed by Windmeijer (2005) (columns IV and VIII). All of the regressions are estimated with an intercept term. Standard errors and $p$-values of Hansen statistics are in round brackets. Degrees of freedom are in square brackets.

$^{*}$ $p < 0.10$;
$^{**}$ $p < 0.05$;
$^{***}$ $p < 0.01$.

**Table 7**
The impact of VC investments on European high-tech entrepreneurial firms' growth: the role of syndication.

| | Sales growth | | Employee growth | |
|---|---|---|---|---|
| | OLS | FE | OLS | FE |
| Column | I | II | III | IV |
| **Panel A: Syndication vs. no VC financing** | | | | |
| LnSize ($t-1$) | −0.2207*** (0.0687) | −0.4412*** (0.0956) | −0.0507** (0.0218) | −0.4300*** (0.0571) |
| LnAge ($t$) | 0.2594 (0.1652) | −0.3617 (0.4539) | −0.0313 (0.0971) | −0.4517* (0.2588) |
| VCSyndicate ($t-1$) | 0.1534 (0.1772) | 0.1561 (0.3019) | 0.1372* (0.0760) | 0.1948 (0.1395) |
| Time dummies | Yes | Yes | Yes | Yes |
| Country dummies | Yes | – | Yes | – |
| Industry dummies | Yes | – | Yes | – |
| Obs. | 249 | 249 | 312 | 312 |
| Groups | 37 | 37 | 44 | 44 |
| $R^2$ | 0.2574 | 0.0732 | 0.1819 | 0.0253 |
| **Panel B: Syndication with GVC or IVC leadership vs. no VC financing** | | | | |
| LnSize ($t-1$) | −0.2176*** (0.0622) | −0.4252*** (0.0940) | −0.0572** (0.0213) | −0.4211*** (0.0574) |
| LnAge ($t$) | 0.2794* (0.1390) | −0.3647 (0.4582) | −0.0273 (0.0927) | −0.4302 (0.2581) |
| GVCLeader ($t-1$) | 0.0096 (0.2172) | −0.0194 (0.4035) | 0.0442 (0.1202) | 0.0723 (0.2473) |
| IVCLeader ($t-1$) | 0.5074** (0.2013) | 0.5987* (0.3320) | 0.2123** (0.0877) | 0.2097 (0.1628) |
| Time dummies | Yes | Yes | Yes | Yes |
| Country dummies | Yes | – | Yes | – |
| Industry dummies | Yes | – | Yes | – |
| Obs. | 249 | 249 | 312 | 312 |
| Groups | 37 | 37 | 44 | 44 |
| $R^2$ | 0.2917 | 0.0999 | 0.1974 | 0.0274 |

The dependent variables are the sales growth (columns I–II) and employee growth (columns III–IV). Country, industry and time dummies are included in the estimates (coefficients are omitted in the table). The estimates are derived from OLS regressions with standard errors that are robust to heteroskedasticity through the Huber-White method and serial correlation within firms (columns I and III) and FE regressions with robust standard errors (columns II and IV). All of the regressions are estimated with an intercept term. Standard errors are in round brackets.
* $p<0.10$;
** $p<0.05$;
*** $p<0.01$.

the magnitude and statistical significance of the dummy variable remain almost the same as before (+53.5%, again close to significance), but the coefficient of the cumulated VC amount that was received from $t-3$ to $t-1$ is now positive and statistically significant at 5%. Thus, it appears that the impact of the syndicates that are led by IVCs on the sales growth is at least partially due to capital injections.[15]

#### 6.1.2. Long-run effects

Based on the estimates of Table 5 (columns II and IV) and Table 7 (Panel B, column II), we computed the long-run effect of being IVC-, GVC- and VC-syndicate-backed on sales and employee growth through FE and GMM-SYS regressions, respectively. We use the following expression:

$$\hat{E}_{VC(\infty)} = \lim_{T\to\infty} \hat{E}_{VC(T)} = \frac{\psi}{|\alpha_1|}. \quad (2)$$

As shown in Table 9, the estimated sales increase of the IVC-backed firms ranges between +60% and +122%, where the FE estimates represent the lower bound of this impact (the long-run effect computed with the bias-corrected LSDV is +63%; for more details, see footnote 13). These long-run effects are statistically significant at 1%. Conversely, we do not detect a statistically significant long-run effect of IVC backing on employee growth. With regard to GVC-backed firms, there is not a positive and significant impact, regardless of the growth measure that is employed. Finally, we find a positive and significant long-run effect of syndicated investments on the sales growth (+141%, which is significant at 10%) when the focal IVC investor is the leading partner.[16] These results are consistent with those provided in Section 5.

### 6.2. Robustness checks

To further test the robustness of the results shown in Section 5, we perform several checks.

First, the use of a step variable to model the VC backing implicitly assumes that 'there is no anticipation effect and no delayed response' of the treatment variable, as suggested by Laporte and Windmeijer (2005: p. 390). Following the authors' recommendations, we test if the average yearly impact of the VC variables on the firm growth hides some important differences over time. From the estimates of Tables 5 and 7 (Panel A), we remove the VC-step variable from our specification(s) and insert a series of impulse dummies from the year before the VC funding to 4 years after the VC funding. We also add a type of 'long-term variable', i.e., a step variable that equals 1 from the fifth year after the VC funding onward. As shown in Table 10, IVC-backed firms outperform their matched sample of non-VC-backed firms in terms of the sales growth in the first 2 years after the VC funding (+33.6% and +42.8%, respectively, both significant at 5%). More interestingly, this increase in the sales value is more pronounced in the long term (+48.3%, significant at 5%). Regarding the employee growth, we find a positive and significant effect of the IVC only in the first year after the VC funding (+22.4%, significant at 1%), while the coefficients for all of the subsequent years are largely not significant. With regard to the GVC-backed and VC syndicate-backed firms, we do not detect any strong positive and significant impact either on the sales or on the employee growth before, during or after the first VC round. As a

[15] Usually, IVC-led syndicate-backed firms receive more financial resources (median value: 1514.050 k€) than IVC-backed (1425.944 k€) and GVC-backed firms (211.467 k€). This evidence might help to explain the result, and it suggests that the financial effects on the firms' growth are produced for only sizeable VC investments.

[16] To estimate long-run effects, we cannot use the estimated coefficients of $LnSize_{i,t-1}$ in GMM-SYS specifications where such coefficients are not statistically different from zero.

**Table 8**
The impact of IVC and GVC investments on European high-tech entrepreneurial firms' growth: exploring 'value-adding' and financial effects.

| Column | FE<br>I | GMM-SYS<br>II | FE<br>III | GMM-SYS<br>IV | FE<br>V |
|---|---|---|---|---|---|
| | IVC vs. no VC financing | | GVC vs. no VC financing | | Syndication vs. no VC financing |
| **Panel A: VC amount [$t-1$]** | | | | | |
| LnSize ($t-1$) | $-0.6387^{***}$ (0.0472) | $-0.3078^{***}$ (0.0670) | $-0.5019^{***}$ (0.0594) | $-0.3128^{**}$ (0.1266) | $-0.4275^{***}$ (0.0953) |
| LnAge ($t$) | 0.1047 (0.1775) | −0.0692 (0.1323) | 0.0071 (0.2791) | 0.0679 (0.2601) | −0.3696 (0.4557) |
| IVC ($t-1$) | $0.3959^{***}$ (0.1228) | $0.3059^{***}$ (0.1154) | – | – | – |
| GVC ($t-1$) | – | – | 0.1092 (0.1511) | 0.0295 (0.1168) | – |
| Syndicate IVC Leader ($t-1$) | – | – | – | – | 0.5267 (0.3473) |
| Syndicate GVC Leader ($t-1$) | – | – | – | – | −0.0617 (0.3995) |
| VC Amount ($t-1$) | −0.0057 (0.0145) | 0.1026 (0.1109) | $-0.0403^{*}$ (0.0237) | −0.0198 (0.0407) | 0.0301 (0.0340) |
| Time dummies | Yes | Yes | Yes | Yes | Yes |
| Country dummies | – | Yes | – | Yes | – |
| Industry dummies | – | Yes | – | Yes | – |
| Obs. | 2143 | 2143 | 882 | 882 | 249 |
| Groups | 325 | 325 | 114 | 114 | 37 |
| $R^2$ | 0.1184 | – | 0.0983 | – | 0.0981 |
| AR (1) | – | $-4.04^{***}$ | – | $-1.93^{*}$ | – |
| AR (2) | – | −0.16 | – | −0.22 | – |
| Hansen | – | 37.56 [36] | – | 33.88 [39] | – |
| **Panel B: Cumulated VC amount [$t-1$; $t-3$]** | | | | | |
| LnSize ($t-1$) | $-0.5663^{***}$ (0.0557) | $-0.2345^{***}$ (0.0684) | $-0.4557^{***}$ (0.0787) | $-0.3331^{***}$ (0.0995) | $-0.3743^{***}$ (0.1001) |
| LnAge ($t$) | 0.0673 (0.2095) | 0.0491 (0.1045) | 0.0225 (0.4973) | 0.1810 (0.1517) | −0.7991 (0.6690) |
| IVC ($t-1$) | $0.3192^{***}$ (0.1099) | $0.3376^{***}$ (0.1168) | – | – | – |
| GVC ($t-1$) | – | – | 0.1176 (0.1505) | 0.0947 (0.1163) | – |
| Syndicate IVC Leader ($t-1$) | – | – | – | – | 0.5348 (0.4256) |
| Syndicate GVC Leader ($t-1$) | – | – | – | – | −0.1099 (0.5929) |
| VC Amount ($t-1$; $t-3$) | 0.0011 (0.0098) | 0.0010 (0.0078) | −0.0005 (0.0106) | $-0.0325^{*}$ (0.0186) | $0.0295^{**}$ (0.0136) |
| Time dummies | Yes | Yes | Yes | Yes | Yes |
| Country dummies | – | Yes | – | Yes | – |
| Industry dummies | – | Yes | – | Yes | – |
| Obs. | 1808 | 1808 | 751 | 751 | 217 |
| Groups | 300 | 300 | 109 | 109 | 36 |
| $R^2$ | 0.0451 | – | 0.0400 | – | 0.0334 |
| AR (1) | – | $-3.00^{***}$ | – | $-2.38^{**}$ | – |
| AR (2) | – | 0.59 | – | 1.09 | – |
| Hansen | – | 40.23 [35] | – | 23.16 [38] | – |

The dependent variable is the sales growth. Country, industry and time dummies are included in the estimates (coefficients are omitted in the table). The estimates are derived from FE regressions with robust standard errors (columns I, III and V), and GMM-SYS with 'collapsed' instruments with finite-sample correction for the two-step covariance matrix developed by Windmeijer (2005) (column II and IV). All of the regressions are estimated with an intercept term. Standard errors are in round brackets. Degrees of freedom are in square brackets.
* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$.

very minor exception, we find that the VC syndicate-backed firms show a growth in the employees that is 28.2% higher than their matched counterparts 2 years after the VC funding (the coefficient is significant at 10%). For the sake of completeness, in unreported regressions (but available upon request from the authors), the same exercise on the 'anticipated and delayed' responses was run, distinguishing syndicates according to the identity of the leader. The analysis confirms that only the IVC-led syndicates produce a positive and significant effect on the sales growth of the entrepreneurial firms, with most of the effect concentrated at approximately 1 year after the first VC investment. Finally, we also conduct the tests that were suggested by Chemmanur et al. (2011: p. 4059). More specifically, we compute the net 'post VC investment' effect year-by-year for each of our three matched samples of VC-backed firms

**Table 9**
Long-run effects of IVC and GVC investments on firm growth over time.

| | Sales growth | | Employee growth | |
|---|---|---|---|---|
| | FE | GMM-SYS | FE | GMM-SYS |
| IVC | $0.6004^{***}$ (0.1814) | $1.2173^{***}$ (0.4463) | 0.2214 (0.1693) | – |
| GVC | 0.1026 (0.2956) | 0.1319 (0.4405) | −0.2895 (0.2879) | – |
| Syndicate IVC Leader | $1.4081^{*}$ (0.8134) | – | 0.4981 (0.3905) | – |
| Syndicate GVC Leader | −0.0456 (0.9507) | – | 0.1718 (0.5876) | – |

The long-run effect of IVC and GVC investments is reported. We refer to the long-run effect calculated from FE regressions with robust standard errors and GMM-SYS regressions with 'collapsed' instruments with finite-sample correction for the two-step covariance matrix developed by Windmeijer (2005) reported in Table 5 (columns II and IV for sales growth and columns VI and VIII for employee growth, respectively) and Table 7 (Panel B, columns II for sales growth and IV for employee growth, respectively). The GMM-SYS results are reported only if the estimated coefficient of $LnSize_{i,t-1}$ is significantly different from zero at conventional confidence levels. Standard errors in round brackets.
* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$.

**Table 10**
Firm growth dynamics around the year of VC funding.

| Column | Sales growth | | | Employee growth | | |
|---|---|---|---|---|---|---|
| | I<br>IVC vs. no VC financing | II<br>GVC vs. no VC financing | III<br>Syndication vs. no VC financing | IV<br>IVC vs. no VC financing | V<br>GVC vs. no VC financing | VI<br>Syndication vs. no VC financing |
| LnSize ($t-1$) | −0.6391*** (0.0474) | −0.5078*** (0.0591) | −0.4358*** (0.1016) | −0.4170*** (0.0475) | −0.3581*** (0.0323) | −0.4124*** (0.0548) |
| LnAge ($t$) | 0.0969 (0.1743) | −0.0286 (0.2833) | −0.3232 (0.4568) | −0.0490 (0.0880) | −0.1098 (0.1187) | −0.4697* (0.2449) |
| IVC Before (1) | 0.0560 (0.1765) | – | – | 0.0448 (0.0801) | – | – |
| IVC (0) | −0.0268 (0.1811) | – | – | 0.1086 (0.0994) | – | – |
| IVC After (1) | 0.3361** (0.1702) | – | – | 0.2241*** (0.0852) | – | – |
| IVC After (2) | 0.4280** (0.1678) | – | – | 0.0935 (0.0854) | – | – |
| IVC After (3) | 0.2716 (0.1765) | – | – | 0.1414 (0.1014) | – | – |
| IVC After (4) | 0.0116 (0.1063) | – | – | −0.0151 (0.0347) | – | – |
| IVC After (≥5) | 0.4833** (0.2006) | – | – | 0.1227 (0.1016) | – | – |
| GVC Before (1) | – | −0.1634 (0.1585) | – | – | 0.0321 (0.1361) | – |
| GVC (0) | – | −0.1318 (0.2498) | – | – | 0.1047 (0.1726) | – |
| GVC After (1) | – | −0.2547 (0.2475) | – | – | −0.0164 (0.1790) | – |
| GVC After (2) | – | −0.0121 (0.2427) | – | – | −0.0741 (0.1819) | – |
| GVC After (3) | – | 0.0651 (0.2317) | – | – | −0.0660 (0.1941) | – |
| GVC After (4) | – | −0.0721 (0.0900) | – | – | −0.0398 (0.0607) | – |
| GVC After (≥5) | – | 0.0598 (0.2477) | – | – | 0.0151 (0.1961) | – |
| SYND Before (1) | – | – | −0.3106 (0.5405) | – | – | 0.0515 (0.2246) |
| SYND (0) | – | – | −0.2526 (0.7335) | – | – | −0.0915 (0.1881) |
| SYND After (1) | – | – | 0.0972 (0.5352) | – | – | 0.2047 (0.2242) |
| SYND After (2) | – | – | −0.1626 (0.5423) | – | – | 0.2816* (0.1487) |
| SYND After (3) | – | – | −0.2110 (0.5546) | – | – | 0.0753 (0.1964) |
| SYND After (4) | – | – | −0.3191 (0.3434) | – | – | 0.0157 (0.0694) |
| SYND After (≥5) | – | – | −0.2668 (0.6036) | – | – | −0.0003 (0.1658) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 2143 | 882 | 249 | 2375 | 964 | 312 |
| Groups | 325 | 114 | 37 | 342 | 123 | 44 |
| $R^2$ | 0.1198 | 0.0957 | 0.0724 | 0.0429 | 0.0327 | 0.0292 |

The dependent variables are the sales growth (columns I–III) and employee growth (columns IV–VI). Time dummies are included in the estimates (the coefficients are omitted in the table). The estimates are derived from FE regressions with robust standard errors. All of the regressions are estimated with an intercept term. Standard errors are in round brackets.

* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$.

relative to the year prior to the VC funding. Overall, these results are fully in line with those shown above and are not reported here for the sake of brevity (they are available upon request from the authors).

Second, even though the results of the above exposed robustness check proposed by Laporte and Windmeijer (2005) appear to exclude reverse causality concerns, we perform several additional 'placebo leads' tests (Bartel and Harrison, 2005; Samila and Sorenson, 2011) by introducing into our FE regressions the leads (at time $t$ and $t+1$) of the VC-step dummies of interest. The results confirm the positive impact of the IVCs (and the syndicates led by the IVCs) on the sales growth and provide further evidence that this impact is truly additional and unlikely to be driven by reverse causality concerns. In fact, all of the $F$ tests do not reject the null hypothesis of the joint insignificance of the leads at time $t$ and $t+1$ of the VC-step variables (the results are reported in Appendix C).

Third, the VICO dataset is an unbalanced panel dataset. As suggested by Semykina and Wooldridge (2010), this unbalancing could be caused by a sample selection issue. More specifically, firm exit dynamics could bias our estimated results. In the VICO dataset, the firms (potentially) exit and are not observed anymore because of two distinct events that include the i) failure or ii) acquisition by another firm. Our three matched samples 'IVC vs. no VC financing', 'GVC vs. no VC financing' and 'Syndication vs. no VC financing' include 58 (46), 19 (2) and 8 (0) failed (acquired) firms, respectively. Both of these events could be influenced, either positively or negatively, by the presence of VC. For example, Puri and Zarutskie (2012) show that VC i) positively impacts the likelihood that firms are acquired and ii) significantly reduces the probability of failure. If there is a significant correlation (either positive or negative) between VC financing and exit and the likelihood of exit is significantly correlated with the firm growth, then our estimates would be biased. Following Wooldridge (1995) and Semykina and Wooldridge (2013), we implement two tests for detecting a potential survivorship bias in our data (for more details, see Appendix D). The results show that the coefficient of the exit bias control term (the inverse Mills ratio on the firm exit, IMR) is never significant, which excludes the presence of any remarkable survivorship bias in our estimates.

Fourth, in our main estimations, we do not account for legal and institutional differences across the countries. To face this issue, in Table 11, we re-estimate the regressions that are shown in Table 5 (columns I and V) and Table 7 (Panel A, columns I and III), substituting the country dummies with the following country-level variables suggested by Cumming and Walz (2010): (i) a measure of the tendency of the firms and accountants to report economic gains faster than economic losses, which is negatively related to accounting conservatism (*Country Earnings Aggressiveness Index*); (ii) a measure of accounting disclosure measures, which is positively related to disclosure (*Country Disclosure Level Index*); and (iii) a measure of accounting standards for earning management in private firms, which is negatively related to accounting disclosure (*Private Firm Accounting Aggregate Index*).[17] We see that in sales growth regressions (columns I–III), there is a positive and statistically significant (at 1% confidence level) impact of accounting disclosure measures and accounting standards for earnings management on the performance of IVC-backed companies (column I), while there is a positive impact of accounting conservatism on the performance of GVC-backed companies (column II). In the employee growth equations (columns IV–VI), the accounting conservatism and accounting disclosure of the countries exert a positive and statistically

[17] For more details on the calculation of the three legal and institutional variables, see Bhattacharya et al. (2003, Table I) and Burgstahler et al. (2006, Table I). We are grateful to an anonymous referee for this suggestion.

**Table 11**
Legal and institutional differences across countries.

| Column | Sales growth | | | Employee growth | | |
|---|---|---|---|---|---|---|
| | I | II | III | IV | V | VI |
| | IVC vs. no VC financing | GVC vs. no VC financing | Syndication vs. no VC financing | IVC vs. no VC financing | GVC vs. no VC financing | Syndication vs. no VC financing |
| LnSize ($t-1$) | −0.1495*** (0.0206) | −0.1237*** (0.0294) | −0.1856** (0.0679) | −0.0478*** (0.0121) | −0.0363** (0.0141) | −0.0490** (0.0203) |
| LnAge ($t$) | −0.2091*** (0.0500) | −0.2293** (0.0954) | 0.3431* (0.1762) | −0.1273*** (0.0201) | −0.1333*** (0.0346) | −0.0209 (0.0906) |
| IVC ($t-1$) | 0.2143*** (0.0531) | – | – | 0.0949*** (0.0257) | – | – |
| GVC ($t-1$) | – | 0.0723 (0.0685) | – | – | 0.0363 (0.0319) | – |
| VCSyndicate ($t-1$) | – | – | 0.1858 (0.1883) | – | – | 0.1362* (0.0757) |
| Country Earnings Aggressiveness Index | 1.8122 (4.6139) | −16.54*** (5.8762) | 7.4326 (17.2429) | −3.8328** (1.9169) | −2.5495 (2.3740) | 2.8334 (5.6547) |
| Country Disclosure Level Index | 0.0201*** (0.0075) | 0.0343 (0.0266) | 0.0168 (0.0332) | 0.0065* (0.0036) | 0.0095 (0.0102) | 0.0133 (0.0132) |
| Private Firm Accounting Aggregate Index | 0.0089*** (0.0030) | 0.0076 (0.0094) | 0.0138 (0.0104) | 0.0013 (0.0013) | 0.0014 (0.0035) | 0.0048 (0.0050) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 2143 | 882 | 249 | 2375 | 964 | 312 |
| Groups | 325 | 114 | 37 | 342 | 123 | 44 |
| $R^2$ | 0.1848 | 0.1832 | 0.2297 | 0.1177 | 0.0983 | 0.1806 |

The dependent variables are the sales growth (columns I–III) and employee growth (columns IV–VI). Industry and time dummies are included in the estimates (coefficients are omitted in the table). The estimates are derived from OLS regressions with standard errors that are robust to heteroskedasticity through the Huber-White method and serial correlation within firms. All of the regressions are estimated with an intercept term. Standard errors are in round brackets.

* $p<0.10$;
** $p<0.05$;
*** $p<0.01$.

significant (at 5% and 10%, respectively) impact on the performance of the IVC-backed companies (column IV). Overall, these results are in line with the evidence shown in the most relevant works in the literature on international business and accounting (see e.g. Bhattacharya et al., 2003; Burgstahler et al., 2006; Cumming and Walz, 2010). With regard to the variables of interest, the results mirror those exposed in Section 5, in terms of both sign and magnitude.[18]

Fifth, one can suspect that the timing of the VC entry could be associated with some intrinsic non-linear effects of age and size in the growth dynamics of the entrepreneurial firms, and in turn, this factor might (at least partly) explain some of our findings. Strictly following the augmented Gibrat law specification proposed by Evans (1987), we estimate an augmented Eq. (1) by introducing as independent variables the squared terms of the logarithms of the size at time $t-1$ and the age at time $t$ and their interaction term.[19] The results of these estimates exposed in Table 12 suggest the presence in some regressions of a non-monotonic relationship between growth and the firm size (see in particular columns I, V and VI), in line with what is commonly found in the literature (Evans, 1987; Almus and Nerlinger, 1999). Conversely, in our sample made prevalently by very young firms (see again Table 4), there does not seem to emerge any strong non-linear pattern of 'liability of youth-golden age-obsolescence', which is instead typical of other more general contexts. More interestingly for our purposes, the estimates reveal that the introduction of these additional terms does not sensibly affect either the magnitude or the statistical significance of the effects of the VC variables of interest.

Sixth, even though we controlled for year dummies, in our main estimates, we do not explicitly account for a potential 'bubble' effect. Thus, in the unreported regressions (which are available upon request from the authors), we re-estimated the models shown in Table 5 (columns II and VI) and Table 7 (Panel A, columns II and IV) before and after the year 2001. These results are in line – both in terms of sign and magnitude – with those exposed in Section 5, in both the pre-bubble and the post-bubble period.

Finally, we re-estimate the models shown in Section 5, winsorizing the sales and headcount values with a 1% cut-off for each tail. In other words, for both variables, we calculated the values that correspond to the 1st and 99th percentiles of each variable's distribution and assigned these values to all of the observations that fell before the 1st percentile and beyond the 99th percentile, respectively. This approach reduces the impact of the outliers and allows the use of a larger number of observations than would be possible if the outliers were deleted. The results adhere to those that were already exposed, and they are available upon request from the authors.

**Table 12**
Potential nonlinearities.

| Column | Sales growth | | | Employee growth | | |
|---|---|---|---|---|---|---|
| | I | II | III | IV | V | VI |
| | IVC vs. no VC financing | GVC vs. no VC financing | Syndication vs. no VC financing | IVC vs. no VC financing | GVC vs. no VC financing | Syndication vs. no VC financing |
| LnSize ($t-1$) | −0.9898$^{***}$ (0.1012) | −0.8519$^{***}$ (0.1349) | −0.3525$^{*}$ (0.1863) | −0.5733$^{***}$ (0.0917) | −0.5127$^{***}$ (0.0917) | −0.4842$^{***}$ (0.1689) |
| LnSize$^2$ ($t-1$) | 0.0302$^{***}$ (0.0099) | 0.0174 (0.0158) | −0.0398$^{**}$ (0.0180) | 0.0197 (0.0130) | 0.0261$^{*}$ (0.0146) | 0.0428$^{**}$ (0.0170) |
| LnAge ($t$) | −0.1865 (0.5355) | −0.1621 (0.6453) | 0.9054 (1.7392) | 0.1011 (0.2167) | −0.4901 (0.3127) | −0.6414 (0.9252) |
| LnAge$^2$ ($t$) | 0.1400 (0.2697) | −0.0536 (0.4337) | −1.1742 (1.0089) | −0.1048 (0.1196) | 0.2475 (0.1961) | 0.1790 (0.5105) |
| LnSize ($t-1$)*Age ($t$) | 0.0239 (0.0426) | 0.1076$^{**}$ (0.0534) | 0.1930$^{**}$ (0.0882) | 0.0263 (0.0253) | 0.0157 (0.0260) | −0.0820 (0.0635) |
| IVC ($t-1$) | 0.3330$^{***}$ (0.1192) | – | – | 0.0908 (0.0762) | – | – |
| GVC ($t-1$) | – | 0.0657 (0.1509) | – | – | −0.0989 (0.1047) | – |
| VCSyndicate ($t-1$) | – | – | 0.0747 (0.3141) | – | – | 0.2260 (0.1441) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 2143 | 882 | 249 | 2375 | 964 | 312 |
| Groups | 325 | 114 | 37 | 342 | 123 | 44 |
| $R^2$ | 0.1459 | 0.1487 | 0.0143 | 0.0393 | 0.0223 | 0.0352 |
| $F$ test | 7.04$^{***}$ [3; 324] | 4.89$^{***}$ [3; 113] | 2.32$^{*}$ [3; 36] | 1.93 [3; 341] | 2.77$^{**}$ [3; 122] | 2.38$^{*}$ [3; 43] |

The dependent variables are sales growth (columns I–III) and employee growth (columns IV–VI). Time dummies are included in the estimates (the coefficients are omitted in the table). The estimates are derived from FE regressions with robust standard errors. All of the regressions are estimated with an intercept term. Standard errors are in round brackets. Degrees of freedom are in square brackets.

$^{*}$ $p<0.10$;
$^{**}$ $p<0.05$;
$^{***}$ $p<0.01$.

[18] For comparison purposes between the results of Tables 5 and 7, we estimated the models in Table 11 by means of OLS regressions. We cannot resort to FE regressions because of the time-unvarying nature of the three legal and institutional variables that were inserted in Table 11. However, we re-estimated the models in Table 5 by substituting the country dummies with the three legal and institutional variables (which correspond to the models in Table 11 in columns I, II, IV and V) through the two GMM specifications explained in Section 5.1. These results are fully in line with those exposed in Table 11 and are available upon request from the authors. We also divide the countries included in the VICO dataset according to the two legal classifications provided by Berkowitz et al. (2003) and Schmidt (2009), respectively. The results are in line with those given in Section 5, even though the significance of the variables of interest is sometimes lower.

[19] In the last row of Table 12, we report the $F$ tests on the null hypothesis that all of the coefficients of the squared terms of the logarithms of the size at time $t-1$ and age at time $t$ and their interaction term are jointly zero. We are grateful to an anonymous referee for suggesting to us this check for non-linearity in the growth equation.

## 7. Conclusions

### 7.1. Implications

The birth and development of entrepreneurial firms in high-tech industries is recognized as one of the main vehicles for revitalizing the European economy, closing the innovation gap with other international competitors, developing a knowledge-based society, and thus propelling 'smart' economic growth, which represents the ultimate objective of European policymakers. It is almost universally contended that a florid VC market in the old continent represents a *sine qua non* condition to realize this goal. Coherently, policymakers at various levels have proposed several policy initiatives to strengthen the VC market in the European landscape. These efforts led to the peculiar feature in Europe with respect to other geographical contexts, the U.S. *in primis*, of a notable presence of VC funds that are directly managed by governmental bodies. Despite this 'direct' presence, the ability of these public funds to accomplish their ultimate goal, i.e., enhancing the growth performance of high-tech entrepreneurial firms, has never been systematically investigated. Furthermore, the above-mentioned ability has never been compared with those of private independent VC investors who operate in the same geographic context. The VICO dataset, which was recently built through a research project funded by the 7th Framework Programme of the European Commission, allows us to investigate this issue for the first time. Our empirical analysis compares the impact of IVC and GVC investors on the sales and employee growth of a representative sample of European high-tech entrepreneurial firms observed from 1993 to 2010. The multiple analyses and the series of robustness checks that we ran point robustly to a positive, statistically significant and economically relevant impact of IVC investors on the real sales growth of high-tech entrepreneurial firms. Conversely, GVC investors are not found to exert any sizeable effect, either in the magnitude or in statistical significance, regardless of the growth measure employed. Our results relegate the direct involvement of GVC investors to be positive in terms of the firm growth only when they are non-leading partners in a VC syndicate. In all of the other cases, whether the GVC investors are alone in the equity capital of a portfolio firm or their involvement precedes or follows the involvement by IVC investors, GVC involvement does not impact on the sales and employee growth of European high-tech entrepreneurial firms. Our findings echo those obtained by Brander et al. (2012), who analyze a large sample of VC-backed firms. They found that the performance of syndicated-backed firms increases if GVC investors have a minority position rather than when they are leaders.

Overall, our analysis sheds a negative light on the government's ability to support high-tech entrepreneurial firms by operating directly in the VC market. The straightforward policy implication that can be drawn from our analysis is: if the European VC industry ever needed governmental aid (and our analysis is not intended to solve this puzzling question), public intervention would preferably create a favorable environment for private VC initiatives through indirect forms of support[20] rather than adopt a 'hands-on-approach'. Recent EU policy initiatives are in line with this approach (e.g., eliminating any unfavorable tax treatment to EU cross-border VC activities; see the European Commission 'Single Market Act I', April 2011), and our work provides an empirical validation for this type of indirect intervention. On the other hand, if one wants to conserve the rationale for a direct public intervention to sustain the growth of high-tech entrepreneurial firms, these findings call for a deep re-consideration of the way that European GVCs are managed. In this respect, our analysis suggests that the inefficacy of GVCs in fostering the (sales) growth of European high-tech entrepreneurial firms is not only related to the scarce availability of financial resources but also might be due to a lack of value-added skills. A solution might be to replicate the design of the Australian IIFs, a specific type of public-private co-investment model that resembles the US and the Israeli programs, which were proven to be effective in enhancing the investments in the start-up and early-stage high-tech entrepreneurial firms and, more generally, in fostering the development of the Australian VC industry.

### 7.2. Directions for future research

This work aims at offering a general assessment on the firm growth-enhancing role that is exerted by GVC and IVC investors on the European high-tech entrepreneurial firms. However, much remains to be investigated through additional and more specific analyses. Specifically, we have not considered in this paper the 'investor perspective'. Preliminary evidence based on the VICO dataset reveals that IVC-backed companies have better exit performance than GVC-backed companies; however, at the same time, there could be important synergistic effects that are produced by mixed-syndicates of IVC and GVC investors in influencing a positive outcome of the investment through a firm's trade sales or an initial public offering (Cumming et al., 2013).

In parallel, we are currently investigating if, beyond the general GVC's inability to foster the firm growth documented here, there could be important composition effects at work. In other words, we are analyzing whether the impact of GVCs on portfolio firms is likely to depend on several characteristics of both governmental investors and portfolio firms. Two important dimensions figure prominently in our research agenda: the young age (or the thin track record) of the portfolio firm and the differences within each VC type. With regard to the former aspect, IVCs usually wait to support ventures until they are capable of presenting a commercial prototype of a product or a service (Block, 2008; Mazzucato, 2011). In this respect, one could hypothesize that GVC investors could exert a 'signaling' function toward third parties (including IVCs) and that the exerted signal is stronger for a younger recipient firm because of its lack of a track record. In this domain, using the VICO dataset, Grilli and Murtinu (2013) show that the reception of a GVC investment in the early stages of life does not strongly influence a venture's market penetration performance, but more detailed investigations are warranted on the presence and nature of a possible enabling function of public funds toward relationships with third parties (e.g., partners, financiers, consumers). With regard to the differences within each VC type, the extant works in the field found significant variations in terms of the reputation capital (Lerner, 1994a; Gompers, 1996; Hsu, 2004; Hochberg et al., 2007; Sørensen, 2007; Nahata, 2008), fund size (Kaplan and Schoar, 2005; Cumming, 2008; Cumming and Dai, 2011) and limited attention of the investors (Cumming and Dai, 2011). In our sample, as preliminary qualitative evidence, we found that there is some degree of within-heterogeneity in the impact on the firm growth of each VC type. With regard to GVC investors, this effect might be due to several dimensions, including different structural characteristics of the funds (for example, in terms of the percentage of public limited partnerships in the total fundraising), dissimilar fund managers' human capital and experience, diverse geographic mandates, investment duration, and contractual clauses (e.g., voting rights). While individuating which dimensions might magnify or hamper the GVC performance and why this result could occur

[20] There is a rich theoretical and empirical literature that is aimed at individuating the most appropriate indirect policy measures to sustain the VC industry. The most investigated dimensions range from labor market reforms (e.g., Jeng and Wells, 2000) to tax incentives (e.g., Keuschnigg and Nielsen, 2002; Keuschnigg, 2004). While the general contention points to the usefulness of such measures on average, the debate is still very lively, as testified by Cumming (2011).

**Table A.1**
Summary of balancing tests.

| | IVC vs. no VC financing | | GVC vs. no VC financing | | Syndication vs. no VC financing | |
|---|---|---|---|---|---|---|
| | Before matching | After matching | Before matching | After matching | Before matching | After matching |
| | | | **Panel A** | | | |
| **Country** | | | | | | |
| Belgium | 0.008 | 1.000 | 0.693 | 0.819 | 0.412 | 1.000 |
| Finland | 0.142 | 0.336 | 0.102 | 0.438 | 0.126 | 1.000 |
| France | 0.030 | 0.562 | 0.285 | 0.596 | 0.138 | 0.748 |
| Germany | 0.009 | 0.400 | 0.081 | 0.614 | 0.771 | 1.000 |
| Italy | 0.113 | 0.349 | 0.037 | 0.755 | 0.166 | 0.323 |
| Spain | 0.017 | 0.110 | 0.000 | 0.572 | – | – |
| United Kingdom | 0.999 | 0.224 | – | – | 0.038 | 1.000 |
| **Industry** | | | | | | |
| Pharmaceutical | 0.104 | 0.147 | 0.476 | 0.700 | – | – |
| ICT manufacturing | 0.019 | 0.886 | 0.511 | 1.000 | 0.625 | 0.689 |
| TLC | 0.909 | 1.000 | 0.189 | 0.384 | – | – |
| Internet | 0.000 | 0.651 | 0.462 | 1.000 | 0.913 | 0.155 |
| Software | 0.015 | 0.286 | 0.090 | 0.718 | 0.262 | 0.373 |
| Biotech | 0.000 | 0.313 | 0.000 | 0.629 | 0.006 | 1.000 |
| **Year** | | | | | | |
| 1994 | 0.575 | 1.000 | 0.001 | 0.313 | – | – |
| 1995 | 0.292 | 0.563 | 0.000 | 0.548 | – | – |
| 1996 | 0.773 | 0.430 | 0.000 | 0.772 | – | – |
| 1997 | 0.764 | 0.262 | 0.000 | 0.260 | – | – |
| 1998 | 0.980 | 1.000 | 0.700 | 1.000 | 0.628 | 0.155 |
| 1999 | 0.349 | 0.732 | 0.115 | 1.000 | 0.569 | 1.000 |
| 2000 | 0.000 | 0.269 | 0.894 | 0.333 | 0.216 | 1.000 |
| 2001 | 0.130 | 0.360 | 0.761 | 1.000 | 0.403 | 0.333 |
| 2002 | 0.199 | 0.398 | 0.166 | 0.413 | 0.629 | 0.305 |
| 2003 | 0.000 | 0.176 | 0.132 | 0.514 | 0.595 | 1.000 |
| 2004 | 0.022 | 0.176 | 0.029 | 1.000 | 0.099 | 0.561 |
| **Age** | 0.000 | 0.383 | 0.000 | 0.509 | 0.010 | 1.000 |
| **Employees** | 0.419 | 0.938 | 0.565 | 0.988 | 0.696 | 0.618 |
| | | | **Panel B** | | | |
| **Pseudo $R^2$** | 0.099 | 0.036 | 0.152 | 0.042 | 0.088 | 0.049 |
| **LR chi²** | 214.26 | 17.96 | 131.29 | 7.41 | 30.49 | 2.69 |
| **$p$ > chi²** | 0.000 | 0.760 | 0.000 | 0.998 | 0.016 | 0.999 |

Panel A refers to the $p$-values of the $t$-tests for the equality of the means before and after the matching for each variable that was used as a covariate in the matching procedures. Panel B reports: (i) pseudo $R^2$ obtained by means of logit regressions on the treatment variables (i.e., the VC funding) before and after the matching; (ii) LR tests on the joint insignificance of covariates included in the logit regressions before and after the matching; and (iii) $p$-values referred to the LR tests.

represents both a theoretical and an empirical challenge, it is clear that the detection of such dimensions would recover a *raison d'être* for a governmental direct intervention in the VC market.

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## Appendix A. Matching procedure(s) and description of matched samples

In Section 4.1, we defined three different categories of VC-backed firms: (1) the IVC-backed firms; (2) the GVC-backed firms; and (3) the VC syndicate-backed firms. As a first step, following the suggestions of Dehejia and Wahba (2002), we randomized our dataset. Second, we chose whether to use a PSM with or without replacement. We opted for matching without replacement because of the sufficient number of control group firms (Dehejia and Wahba, 2002) that acted as potential matches of the VC-backed firms. The drawbacks of our choice are: (i) a potential increase in the bias; and (ii) a sensitivity of the goodness of the procedure to the order of the firms in the dataset (Rosenbaum, 1995). With regard to the latter, as previously explained, we randomized the dataset. Regarding the potential high level of the bias, we performed a balancing test on the variables that are included in the PSM (Table A.1, Panel A).

Once we decided to use a PSM without replacement, we had to choose how many control group firms to match with each VC-backed firm. Following Puri and Zarutskie (2012), we chose a one-to-one matching. Therefore, we built three matched samples of non-VC-backed firms that are comparable to the sample of VC-backed firms according to a set of a priori characteristics (the samples are labeled as: 'IVC vs. no VC financing', 'GVC vs. no VC financing' and 'Syndication vs. no VC financing'). In particular, the propensity scores were obtained by estimating a logit model in the year of the first VC round in which the dependent variable is the probability of receiving VC and the independent variables include the firm age, firm size (number of employees), country and industry dummies. Abadie and Imbens (2006) claim that there is a trade-off in estimating PSM with balanced or unbalanced numbers of control group observations. As a robustness check, we performed a nearest-match method with replacement and selected one, two or three control observations for each VC-backed firm, alternatively. We also performed a caliper matching with replacement (with one, two or three control group observations) for a range of radius values. The results were almost unchanged.

In Table A.1, we report $t$-tests for the equality of means before and after matching for all of the covariates that are used in matching procedures (Panel A) and other tests to verify the correctness of our procedure (Panel B). In Panel A, we verify whether the specification of the propensity scores that we chose allows us to 'balance'

**Table B.1**
Pseudo-first stage regressions.

| | Sales growth | | | | Employees growth | | | |
|---|---|---|---|---|---|---|---|---|
| | IVC vs. no VC financing | | GVC vs. no VC financing | | IVC vs. no VC financing | | GVC vs. no VC financing | |
| Equation: | Differences I | Levels II | Differences III | Levels IV | Differences V | Levels VI | Differences VII | Levels VIII |
| $H_0: \forall\tau: \beta_\tau = 0$ | 4.64*** | 101.15*** | 1.48 | 17.68*** | 6.87*** | 88.37*** | 3.57** | 19.83*** |
| Adjusted $R^2$ | 0.0379 | 0.2063 | 0.0966 | 0.1011 | 0.0551 | 0.1613 | 0.0984 | 0.0675 |

The first line reports $F$ statistics on the null hypothesis of weak instruments.
* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$.

**Table B.2**
First-stage regressions: TSLS.

| | IVC vs. no VC financing | | | GVC vs. no VC financing | | | Syndication vs. no VC financing | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coef. I | KP LM II | KP Wald $F$ III | Coef. IV | KP LM V | KP Wald $F$ VI | Coef. VII | KP LM VIII | KP Wald $F$ IX |
| **Panel A: Sales growth** | | | | | | | | | |
| TTA | 0.0913 (0.0712) | 1.632 | 1.645 | 0.1386 (0.0890) | 2.349 | 2.427 | −0.2275 (0.8451) | 0.078 | 0.072 |
| GDP growth | 0.0158 (0.0133) | 1.400 | 1.398 | 0.0026 (0.0106) | 0.062 | 0.060 | 0.0366 (0.0384) | 0.941 | 0.907 |
| IVC fundraising | −0.0000 (0.0001) | 0.330 | 0.327 | – | – | – | – | – | – |
| IPO | 0.0002 (0.0002) | 1.379 | 1.375 | −0.0002 (0.0006) | 0.144 | 0.143 | −0.0014** (0.0005) | 6.090 | 6.361 |
| IPO/GDP | 0.0000* (0.0000) | 3.539 | 3.621 | – | – | – | – | – | – |
| **Panel B: Employee growth** | | | | | | | | | |
| TTA | 0.1448** (0.0599) | 5.517 | 5.843 | 0.1019 (0.0741) | 1.784 | 1.890 | −0.3689 (0.6681) | 0.321 | 0.305 |
| GDP growth | 0.0077 (0.0114) | 0.452 | 0.449 | 0.0021 (0.0116) | 0.034 | 0.033 | 0.0063 (0.0335) | 0.039 | 0.036 |
| IVC fundraising | 0.0000 (0.0001) | 0.000 | 0.000 | – | – | – | −0.0001 (0.0001) | 0.243 | 0.228 |
| IPO | 0.0002 (0.0001) | 1.328 | 1.316 | −0.0005 (0.0006) | 0.629 | 0.626 | −0.0011* (0.0006) | 3.281 | 3.421 |
| IPO/GDP | 0.0000 (0.0000) | 2.671 | 2.695 | – | – | – | – | – | – |

First-stage results of the TSLS panel models with fixed effects are reported. We show the coefficient of the focal external instrument (columns I, IV and VII), LM (columns II, V and VIII) and Wald versions of the Kleibergen–Paap statistic (columns III, VI and IX). Standard errors are in round brackets.
* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$.

all of the covariates that are included in the estimation of the propensity scores between the VC-backed firms and the matched non-VC-backed firms. Although we have no balance for many of the covariates before performing the PSM (e.g., age, the biotech industry, and year 2004 in all of the three typologies of VC-backed firms); after PSM, in all of the three matching procedures that we implemented, there is a perfect balance ($p$-values $\geq$0.1 after matching) for all of the covariates. Thus, it is not necessary to implement any further balancing algorithm, as suggested by Dehejia and Wahba (2002: p. 161).

In Panel B, we further tested the 'goodness' of the implemented matching procedures. First, pseudo $R^2$ obtained by estimating the logit models on the matched samples are always lower than pseudo $R^2$ before matching. Second, the $p$-values referred to the LR test on the joint insignificance of the covariates before and after matching reassures us about the functional form that we chose to estimate the propensity scores. In fact, the covariates that are included in the logit models before matching explain the likelihood of obtaining VC funding ($p$-values < 0.05) in all of the three matching procedures. At the same time, such covariates after matching are jointly null (all of the $p$-values are $\geq$0.75).

## Appendix B. Instruments

The assumption that we made about a possible endogeneity of VC implies, in the GMM-SYS approach, that the lagged levels of the VC variables are used as instruments for Eq. (1) in the differences and that the lagged differences of the VC variables are used as instruments for Eq. (1) in the levels. The validity of these instruments has been verified by means of the Hansen tests, as shown in Tables 5 and 6. However, we have also to test that these instruments are not weak, i.e., that they are strongly correlated with the vector $VC_{i,t-1}$. For this purpose, we ran the following pseudo-first stage regressions for the 'difference' part and the 'system' part of the GMM-SYS procedure, respectively[21]:

$$\text{Differences}: \quad \Delta VC_{i,t-1} = \sum_{\tau=t-3}^{t-4} \alpha_\tau LnSize_{i,\tau} + \sum_{\tau=t-3}^{t-4} \beta_\tau VC_{i,\tau} + \gamma \Delta LnAge_{i,t-1} + T_i + \Delta\omega_{i,t-1}$$

$$\text{Levels}: \quad VC_{i,t-1} = \sum_{\tau=t-2}^{t-3} \alpha_\tau \Delta LnSize_{i,\tau} + \sum_{\tau=t-2}^{t-4} \beta_\tau \Delta VC_{i,\tau} + \gamma LnAge_{i,t-1} + C_i + S_i + T_i + \eta_{i,t-1}$$

The two typologies of pseudo-first stage regressions are run on the matched samples 'IVC vs. no VC financing' and 'GVC vs. no VC financing', on each VC variable that is included in the vector $VC_{i,t-1}$. For the sake of simplicity, we report the pseudo-first

[21] We refer to the GMM-SYS specification with moment conditions in the interval between $t-3$ ($t-2$) and $t-4$ ($t-3$) for instruments in levels (differences). See Section 5 for more details.

stage regressions in which the dependent variables are $IVC_{i,t-1}$ and $GVC_{i,t-1}$. Pseudo-first stage regressions on $IVCAfter_{i,t-1}$ and $GVCAfter_{i,t-1}$ are available upon request from the authors. In Table B.1, we report the $F$ tests on the null hypothesis that all of the $\beta_\tau$ coefficients in the differences and in the levels are jointly zero. In each matched sample, the $F$ statistic on the null hypothesis of the weak instruments is rejected both on the $\beta_\tau$ coefficients in the differences and the $\beta_\tau$ coefficients in the levels (with the exception of column III). However, all of the values of the $F$ statistic that are related to the pseudo-first stage regressions run on the 'system' ('difference') part of GMM-SYS procedures are above (below, respectively) the critical value of 10 (Staiger and Stock, 1997), which points to a stronger relevance of the lagged instruments in the first differences and thus to the importance of the additional instruments that are used by the system part of the GMM methodology.

Then, as explained in footnote 10 (Section 5.1), in addition to the GMM-SYS estimation, we also attempted to implement a panel two-stages least squares (TSLS) methodology with fixed effects. The availability of a suitable set of strong external firm-specific instruments is crucial to implementing the methodology. In our setting, this difficult task is even more arduous because the instruments must differentiate VC investors according to their typology. Among the variables that are identified as good candidates on a theoretical basis, we employed the following measures, which were used in previous empirical analyses to instrument VC investments at the firm level: the annual ratio between tangible assets and total assets (TTA) at the industry level (Gompers, 1995; source: the VICO dataset), GDP growth (Jeng and Wells, 2000; source: World Bank), the annual IVC fundraising at the country level (in a similar vein, see Bottazzi et al., 2008; source: the Thomson One database), the annual number of IPOs at the country level, the annual ratio between the number of IPOs at the country-level and the GDP at the country level (in a similar vein, see Jeng and Wells, 2000). In fact, these variables proved to be only marginally correlated with the variables to be instrumented. As shown in Table B.2, these variables are not strongly correlated to *any* of the variables that are to be instrumented: $IVC_{i,t-1}$ in columns I–III; $GVC_{i,t-1}$ in columns IV–VI; and $VCSyndicate_{i,t-1}$ in columns VII–IX. Allegedly, all of the values of the Kleibergen–Paap (2006) statistic do not reject the null hypothesis of weak identification, in both the LM and Wald versions.

## Appendix C. Placebo leads test

The results that are related to the 'placebo leads' tests are presented in Table C.1.

## Appendix D. Survivorship bias

The starting point for testing the possible presence of a survivorship bias in our findings is the procedure developed by Wooldridge (1995). This procedure makes a normality assumption on the errors in the selection (exit) equation. Such errors are allowed to be serially correlated and heteroskedastic. From this equation, the researcher computes the inverse Mills ratio (IMR)-type term (see Wooldridge, 2002: p. 563) that is inserted into the FE estimation of the main equation at the second step using the unbalanced panel. Following Semykina and Wooldridge (2010), for each year, we estimated an exit equation on the overall VICO dataset. The dependent variable in these probit models is a dummy variable that equals 1 in the year that the focal firm exited the VICO dataset. The independent variables included firm-specific characteristics, and the industry and country dummies. For each year, we computed the IMR-type term that was to be added as a control for survivorship

**Table C.1**
'Placebo leads' tests.

| | Sales growth | | | Employee growth | | |
|---|---|---|---|---|---|---|
| | I<br>IVC vs. no VC financing | II<br>GVC vs. no VC financing | III<br>Syndication vs. no VC financing | IV<br>IVC vs. no VC financing | V<br>GVC vs. no VC financing | VI<br>Syndication vs. no VC financing |
| LnSize ($t-1$) | −0.6449*** (0.0481) | −0.4986*** (0.0607) | −0.4348*** (0.1004) | −0.4242*** (0.0494) | −0.3529*** (0.0324) | −0.4345*** (0.0594) |
| LnAge ($t$) | 0.1194 (0.1831) | 0.0163 (0.2898) | −0.3756 (0.4391) | −0.0679 (0.0899) | −0.1341 (0.1139) | −0.4130* (0.2427) |
| IVC ($t+1$) | 0.0569 (0.1767) | – | – | 0.0473 (0.0803) | – | – |
| IVC ($t$) | −0.0995 (0.1366) | – | – | 0.0688 (0.0930) | – | – |
| IVC ($t-1$) | 0.4546*** (0.1552) | – | – | 0.0551 (0.0982) | – | – |
| GVC ($t+1$) | – | −0.1806 (0.1644) | – | – | 0.0211 (0.1349) | – |
| GVC ($t$) | – | 0.0582 (0.2040) | – | – | 0.0713 (0.1334) | – |
| GVC ($t-1$) | – | 0.0599 (0.2100) | – | – | −0.1430 (0.1070) | – |
| VCSyndicate ($t+1$) | – | – | −0.3101 (0.5209) | – | – | 0.0339 (0.2120) |
| VCSyndicate ($t$) | – | – | 0.0523 (0.7384) | – | – | −0.1282 (0.1774) |
| VCSyndicate ($t-1$) | – | – | 0.2418 (0.4520) | – | – | 0.2575 (0.1545) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 2089 | 874 | 241 | 2291 | 946 | 303 |
| Groups | 321 | 114 | 35 | 336 | 122 | 42 |
| $R^2$ | 0.1199 | 0.0961 | 0.0510 | 0.0408 | 0.0283 | 0.0270 |
| 'Placebo leads' $F$ test [$VC_t$; $VC_{t+1}$] | 0.27 [2] | 0.64 [2] | 0.20 [2] | 0.64 [2] | 0.18 [2] | 0.31 [2] |

The dependent variables are the sales growth (columns I–III) and the employee growth (columns IV–VI). Time dummies are included in the estimates (the coefficients are omitted in the table). The estimates are derived from FE regressions with robust standard errors. All of the regressions are estimated with an intercept term. Standard errors are in round brackets. Degrees of freedom are in square brackets.

* $p<0.10$;
** $p<0.05$;
*** $p<0.01$.

**Table D.1**
Survivorship bias tests.

| | FE I | GMM-SYS II | FE III | GMM-SYS IV | FE V |
|---|---|---|---|---|---|
| | IVC vs. no VC financing | | GVC vs. no VC financing | Syndication vs. no VC financing | |
| | | | **Panel A: Sales growth** | | |
| LnSize ($t-1$) | −0.6754*** (0.0440) | −0.2366*** (0.0631) | −0.5441*** (0.0546) | −0.2656*** (0.0926) | −0.5362*** (0.0905) |
| LnAge ($t$) | 0.1898 (0.1742) | −0.2197** (0.0946) | −0.0012 (0.2510) | 0.0340 (0.1928) | −0.1685 (0.4363) |
| IVC ($t-1$) | 0.4561*** (0.1179) | 0.2425** (0.1038) | – | – | – |
| GVC ($t-1$) | – | – | 0.1259 (0.1445) | −0.0028 (0.1293) | – |
| VCSyndicate ($t-1$) | – | – | – | – | 0.1311 (0.2973) |
| IMR ($t$) | 0.2655 (0.2786) | −0.0303 (0.1136) | −0.2183 (0.3536) | −0.0569 (0.2048) | −0.0605 (0.6861) |
| Time dummies | Yes | Yes | Yes | Yes | Yes |
| Country dummies | – | Yes | – | Yes | – |
| Industry dummies | – | Yes | – | Yes | – |
| Obs. | 1943 | 1943 | 755 | 755 | 225 |
| Groups | 324 | 324 | 114 | 114 | 37 |
| $R^2$ | 0.1439 | – | 0.1471 | – | 0.0988 |
| AR (1) | – | −4.00*** | – | −3.66*** | – |
| AR (2) | – | 0.97 | – | −0.18 | – |
| Hansen ($p$-value) | – | 79.15 [71] (0.237) | – | 75.16 [75] (0.473) | – |
| | | | **Panel B: Employee growth** | | |
| LnSize ($t-1$) | −0.4278*** (0.0495) | −0.0566 (0.0399) | −0.3729*** (0.0335) | −0.0436 (0.0459) | −0.4249*** (0.0575) |
| LnAge ($t$) | −0.0766 (0.0900) | −0.1190*** (0.0352) | −0.1012 (0.1169) | −0.1225** (0.0491) | −0.4587* (0.2583) |
| IVC ($t-1$) | 0.0959 (0.0766) | −0.0354 (0.0624) | – | – | – |
| GVC ($t-1$) | – | – | −0.0962 (0.1087) | −0.1353** (0.0638) | – |
| VCSyndicate ($t-1$) | – | – | – | – | 0.1958 (0.1361) |
| IMR ($t$) | −0.0886 (0.1289) | 0.0711 (0.0649) | 0.0718 (0.1800) | 0.0675 (0.0943) | 0.2660 (0.2343) |
| Time dummies | Yes | Yes | Yes | Yes | Yes |
| Country dummies | – | Yes | – | Yes | – |
| Industry dummies | – | Yes | – | Yes | – |
| Obs. | 2342 | 2342 | 934 | 934 | 310 |
| Groups | 342 | 342 | 123 | 123 | 44 |
| $R^2$ | 0.0347 | – | 0.0296 | – | 0.0201 |
| AR (1) | – | −2.98*** | – | −4.72*** | – |
| AR (2) | – | 0.01 | – | 0.19 | – |
| Hansen ($p$-value) | – | 81.06 [70] (0.172) | – | 83.13 [75] (0.244) | – |

The dependent variables are the sales growth (Panel A) and the employee growth (Panel B). Country, industry and time dummies are included in the estimates (the coefficients are omitted in the table). The estimates are derived from FE regressions with robust standard errors, and the GMM-SYS with moment conditions of endogenous variables restricted to the interval $t-3$ ($t-2$) and $t-4$ ($t-3$) for instruments in levels (differences) that have a finite-sample correction for the two-step covariance matrix developed by Windmeijer (2005). All of the regressions are estimated with an intercept term. Standard errors and $p$-values of Hansen statistics are in round brackets. Degrees of freedom are in square brackets.

* $p<0.10$;
** $p<0.05$;
*** $p<0.01$.

bias in the main equation at the second step, as estimated through FE and GMM-SYS. Semykina and Wooldridge (2013) extend their procedure (2010) to avoid the 'weak instruments' problem that is associated with the panel TSLS estimator with fixed effects. With the 'new' procedure, the main equation is estimated in levels and not in differences. As explained in Section 5, we cannot perform the procedure suggested by Semykina and Wooldridge (2010, 2013) on the sample of VC syndicate-backed firms because the conditions to perform the GMM estimations are not met. Note that all of these tests do not require the adjustment of standard errors at the 2° step (Semykina and Wooldridge, 2010). The results of the tests are presented in Table D.1.

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