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The impact of venture capital on the productivity growth of European entrepreneurial firms: 'Screening' or 'value added' effect?

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ABSTRACT

We aim to ascertain to what extent the better performance of European venture capital (VC)-backed firms in high-tech industries is due to either 'screening' or 'value added' provided by VC investors. We compare portfolio firms' productivity growth before and after the first VC round, using a matched control group as benchmark. We show that productivity growth is not significantly different between VC and non-VC-backed firms before the first round of VC financing, whereas significant differences are found in the first years after the investment event. We also find that the value-adding services provided by VC investors 'imprint' the portfolio firm.

1. Executive summary

Entrepreneurial firms may lack financial resources and managerial competences which are fundamental for their economic performance, especially when they operate in high-tech industries (Gans and Stern, 2003). In this respect, venture capital (VC) is considered by both academics and practitioners as one of the key drivers of the success of entrepreneurial firms. Several previous firm-level studies investigated the relationship between VC funding and firm performance. On average, they show that VC-backed firms grow faster, patent more, have higher productivity and are more likely to go public than non-VC-backed ones (Wright and Robbie, 1998).

However, the causality of the impact of VC on firm performance is still a pending research question (Gompers and Lerner, 2001). In other words, the superior performance of VC-backed firms (compared to non-VC-backed ones) might be (at least partially) explained by the 'screening' ability of VC investors. Moreover, even though screening is controlled for, it is important to understand how VC investors foster the performance of portfolio firms: is it the superior performance of VC-backed firms related to the VC funding received or to value-adding activities performed by VC investors? Finally, in the case of a significant 'value-adding effect' on portfolio firms' performance, it is interesting to test whether this effect persists over time or fades away after a few years.

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In this work we aim to fill these gaps. First, to tackle reverse causality problems between VC and firm performance, we perform a matching procedure before the first round of VC funding and we estimate the impact of VC both before and after the first round of VC funding. Second, in order to isolate the 'value-adding effect' from the 'financial effect', we use different productivity growth measures as dependent variables. In fact, by scaling sales growth with the necessary growth in inputs, productivity measures allow us to control for VC funding injections that increase firms' inputs (capital and/or labor). Third, we test whether a value-adding effect exists and, if so, we verify whether VC investors are able to 'imprint' portfolio firms during their holding period. Finally, we test whether the value-adding effect is decreasing over time.

In the empirical section of the paper, we consider a sample of 696 entrepreneurial firms, 267 of which are VC-backed. They are located in six European countries: Belgium, Finland, France, Italy, Spain and the United Kingdom. This sample is extracted from the VICO dataset, a brand new firm-level longitudinal dataset sponsored by the European Union under the 7th Framework Program (for more details, see the official website at: http://www.vicoproject.org). For more details on the procedures used in the data gathering process and on all of the variables included in the dataset, see Bertoni and Martí (2011).

The econometric estimates show that VC-backed firms do not exhibit a significantly different productivity growth to that of their matched non-VC-backed counterparts before the first VC round, thus excluding a screening effect. This is not in line with some previous studies, mostly based on US manufacturing firms. This difference in screening abilities between US and European VC investors might be explained by the higher level of development of US VC market (than that of the European VC market). These results hold when we control for: i) the 'potentially different' growth orientation between VC-backed and matched non-VC-backed firms before VC funding; and ii) the reputation of VC investors. Conversely, productivity growth is significantly higher in VC-backed firms after the first VC round, so confirming a value-adding effect. Moreover, VC-backed firms do not exhibit a decrease in productivity growth measures after the exit of VC investors, suggesting an imprinting effect. Finally, the effect of VC seems to be persistent over time. Our findings are robust, as confirmed by a series of different robustness checks we ran.

To sum up, this study considerably extends our understanding of the impact of VC on the performance of European entrepreneurial firms in high-tech industries. From a policy perspective, this study reveals that VC is a valid tool for improving the performance of European entrepreneurial firms and indirectly to increase the dynamic efficiency of the economic system. Since the business environment in Europe makes it difficult for VC investors to successfully develop and exit entrepreneurial firms, incentive schemes should be further developed to enhance this type of investment.

2. Introduction

Venture capital (VC, henceforth) is generally considered by both academics and practitioners as the most suitable financing mode for entrepreneurial firms. The extant literature has shown how VC investors (VCs, henceforth) play a key role in the screening process (Amit et al., 1998; Chan, 1983; Tyebjee and Bruno, 1984), as well as in the post-investment monitoring of the portfolio firm (Kaplan and Strömberg, 2003; Lerner, 1995; Sahlman, 1990). VCs provide value-adding services (Sapienza et al., 1996; Sørensen, 2007), such as coaching, mentoring and access to investment bankers, which could have signaling effects (Megginson and Weiss, 1991). Furthermore, VC-backed firms benefit from the network of contacts that may be provided by reputable, well-connected VCs (Hsu, 2006; Lindsey, 2008).

Several previous studies evaluated the impact of VC on firm performance. In particular, some studies focused on different measures of firm growth, such as sales and employment growth (e.g. Alemany and Martí, 2005; Bottazzi and Da Rin, 2002; Bottazzi et al., 2008; Davila et al., 2003; Gompers and Lerner, 2001). Regarding productivity measures, Alemany and Martí (2006) used measures of partial productivity (i.e. capital and labor productivities), whereas Chemmanur et al. (2011) and Colombo et al. (2012) resorted to total factor productivity (TFP, henceforth).

However, as highlighted by Gompers and Lerner (2001), one of the pending research questions is the causality of the impact of VC on portfolio firm performance. In fact, the higher performance found in VC-backed firms is related to the presence of VCs in portfolio firm's equity capital, but it might also be explained by the attractiveness of firms with greater business opportunities. In other words, VC-backed firms might be better than non-VC-backed ones before the first round of VC financing. If this is true, then the higher performance of VC-backed firms can be (at least partially) explained by the 'screening' ability of VCs.

In addition, even though screening is controlled for, there could still be some doubts about how VCs foster the performance of portfolio firms. VCs not only provide financial resources but also contribute to enhancing firm performance through value-adding activities. Since the superior performance of VC-backed firms might be solely related to the funding received, which is not easily available to similar firms without VC backing, it is important to isolate these two ('financial' and 'value added') effects. Balboa et al. (2011) address this gap but they neglect to consider screening in their approach.

Furthermore, in the case of a significant value-adding effect on portfolio firms' performance, it is relevant to analyze whether this effect persists over time or fades away after a few years.

In this work we aim to fill these gaps. First, to tackle the abovementioned reverse causality problems, we propose a procedure that allows us to: i) reduce the selection bias problem in our sample by applying a matching procedure before the first round of VC funding; ii) control for reverse causality concerns by estimating the impact of VC both before and after the first round of VC funding. Secondly, in order to isolate the value-adding effect from the financial effect, we focus on productivity growth. In fact, by scaling sales growth with the necessary growth in inputs, productivity measures allow us to control for VC funding injections that increase firms' inputs (capital and/or labor). It is worth noting that considering only output indicators (e.g. growth in sales or employees) without any regard for the cost-side would give us only a partial and incomplete indication of firm performance, and this could lead to wrong conclusions about the net benefits due to VC involvement. As productivity reflects both output performance and efficiency in the use of inputs, it is tailored to measure the impact of VC financing that may have beneficial effects on both sides. In this study, we employ the growth in labor productivity, capital productivity and TFP as performance measures.[1] Third, we test for the existence of a value-adding effect by VCs in portfolio firms and examine different characteristics of such value-adding activities. Primarily, we study whether VC involvement significantly leads to an increase in firm performance. Then we verify whether VCs are able to 'imprint' portfolio firms during their holding period. If they do, such 'imprinting' effect would continue to operate and benefit the portfolio firm, even after the exit of VCs. Finally, we test whether the impact of the value added provided by VCs on firm performance is decreasing over time. In particular, we argue that value-adding services provided by VCs should determine an increase in firm performance especially in the first years after VCs' entry into portfolio firms' equity capital.

Our sample includes 696 entrepreneurial firms, 267 of which are VC-backed. They received their first round of VC funding between 1995 and 2004. Sample firms are located in six European countries, namely Belgium, Finland, France, Italy, Spain and the United Kingdom.

The paper is structured as follows. Section 3 is devoted to the development of our research hypotheses. Section 4 describes the methodology applied to test our hypotheses. Section 5 describes the dataset and the sampling process and shows descriptive statistics on the sample used. Results are reported in Section 6. Section 7 shows further analyses we conducted to test the robustness of our findings. Finally, Section 8 discusses and concludes.

3. Theory and research hypotheses

Entrepreneurial firms may lack commercial and managerial competences (Teece, 1986) which limit their growth and even threaten their survival (Carpenter and Petersen, 2002a), especially when they operate in high-tech industries (Gans and Stern, 2003). Because of the technology-intensive nature of their activity, their lack of a track record and the nature of their assets (which are firm-specific and/or intangible and hence cannot be pledged as collateral), they face severe adverse selection and moral hazard problems in raising external capital (Berger and Udell, 1998; Bertoni et al., 2010; Carpenter and Petersen, 2002b; Denis, 2004).

VC financing is generally considered by both academics and practitioners as the most suitable financing mode for entrepreneurial firms, especially in the earlier stages of their life. Allegedly, VCs are able to 'pick winning firms' that have promising future business opportunities, which are hidden to other investors, and provide them with the financing necessary to realize these opportunities (Amit et al., 1998; Chan, 1983; Tyebjee and Bruno, 1984). However, they also 'build winners' by providing portfolio firms with coaching (Hellmann and Puri, 2002; Jain and Kini, 1995), effective monitoring (Kaplan and Strömberg, 2003; Lerner, 1995; Sahlman, 1990) and valuable business contacts (Hsu, 2006; Lindsey, 2008).

There is a vast theoretical and empirical literature about the impact of VC on firm performance. Firm-level studies targeting European countries have considered different measures of firm performance. On average, they show that VC-backed firms grow faster, patent more, have higher productivity and are more likely to go public than non-VC-backed ones (e.g. Wright and Robbie, 1998).

In particular, in this work we focus on the impact of VCs on portfolio firm performance by considering that, in addition to funding, the positive effect might be explained by two different factors: i) screening; and ii) value added.

3.1. Screening

VCs do not invest randomly; rather they select firms by continuously screening the market in order to find good investment opportunities (e.g. Chan, 1983; Muzyka et al., 1996). As a result, the superior performance of VC-backed firms might be related to the fact that VCs are able to select higher quality firms (Gompers and Lerner, 2001). In fact, VCs are recognized as agents that are better able to address information asymmetry problems than other financial intermediaries, especially when investing in unlisted firms (Amit et al., 1998). As a consequence, VCs' screening ability could be a significant determinant of the superior performance of VC-backed firms (see, among others, Shepherd and Zacharakis, 2002; Tyebjee and Bruno, 1984).[2]

Nevertheless, it is important to consider that VC can also be a signal of high risk investments. Thus, if compared to alternative investments, VC financing may lead to a higher percentage of failures (Gifford, 1997). This survivorship bias may limit the validity of the previous works that looked at surviving VC-backed firms only.[3]

Accordingly, the question to be answered is: Do portfolio firms perform better because of screening activities performed by VCs?

Previous studies, reported in Table 1, provided mixed results on this issue.

[1] The extant entrepreneurship literature has shown that productivity growth is a suitable performance measure for entrepreneurial firms operating in high-tech industries (for a survey, see Colombo et al., 2009).

[2] Our idea of "screening" is slightly different from "sorting" (Sørensen, 2007). As explained by Chemmanur et al. (2011), "screening" refers to the VCs' ability to select better firms in the presence of information asymmetries between VCs and potentially investable firms. Conversely, "sorting" refers to a full information market in which 'better' VCs are matched with better quality firms. Moreover, it is worth noting that we closely adhere to the idea of Chemmanur et al. (2011) by modeling a screening process based on portfolio firms' economic performance (i.e. operating efficiency improvements measured through productivity growth) before VC funding. This idea that VCs screen potentially investable firms on their past economic performance is well grounded in finance (e.g. Chemmanur et al., 2011) and entrepreneurship literature (e.g. Davila et al., 2003). However, we are conscious that: i) VCs might select firms according to their 'potential performance' and not on past performance; and ii) potentially investable firms' growth paths might be related to the characteristics of the environmental settings in which entrepreneurial firms compete (e.g. Clarysse et al., 2011). We address these two issues in Section 7.

[3] We address issues related to the potential presence of survivorship bias in our data in Appendix D.

Table 1
Previous studies on the comparison between screening and value-adding effects of VCs.

Author(s)	Year	Sample	Country	Period	Performance measure	Results
Baum and Silverman	2004	204 biotechnology start-ups	Canada	1991–2000	Sales growth, R&D spending growth, R&D employment growth, number of patent applications, number of patents granted, startup survival	Screening and value added
Chemmanur, Krishnan and Nandy	2011	1881 VC-backed and 185,882 non-VC-backed manufacturing firms	USA	1972–2003	TFP growth	Screening and value added
Engel	2002	1074 start-ups	Germany	1991–1998	Employment growth	Value added
Davila, Foster and Gupta	2003	494 Silicon Valley based startups	USA	1994–1999	Employment growth	Value added
Balboa, Martí and Zieling	2006	250 VC-backed firms in the expansion stage	Spain	1993–2002	Sales and employment growth	Value added
Colombo and Grilli	2010	439 entrepreneurial firms	Italy	1994–2003	Sales and employment growth	Value added
Bertoni, Colombo and Grilli	2011	538 entrepreneurial firms	Italy	1994–2003	Sales and employment growth	Value added

Baum and Silverman (2004) focus on three initial start-up characteristics, namely social capital (alliances), intellectual capital (patents) and human capital (management), and analyze if these have the same influence on the financing decision of the VCs and the post-investment performance of portfolio firms. They suggest that VC-backed startups outperform non-VC-backed ones, but conclude that the question of causality remains unsolved. Chemmanur et al. (2011) find that the efficiency of VC-backed firms, before the first VC round, is higher than that of non-VC-backed counterparts. Furthermore, the growth in efficiency of VC-backed firms after the first VC round is higher than that of non-VC-backed firms.

On the other hand, Davila et al. (2003) show that VC-backed firms grow more than their counterfactual after the initial VC round, but firm growth before VC funding does not attract VC investments. Bertoni et al. (2011) find strong evidence of a significantly higher growth of VC-backed firms, especially on employment. Conversely, they find weak evidence that firm growth before the first VC round leads to a greater likelihood of obtaining access to VC financing. Similar results are obtained by Engel (2002) on a sample of German firms, Balboa et al. (2006) on a sample of Spanish firms, and Colombo and Grilli (2010) on a sample of Italian firms. None of them find any evidence of a positive screening effect.

To sum up, there is mixed evidence on the better performance of VC-backed firms before the first VC round. Nevertheless, based on the predictions of the literature about the superior screening abilities of VCs, we posit the following hypothesis.

Hypothesis 1. The productivity growth of VC-backed firms is significantly higher than that of non-VC-backed ones before the first VC round.

3.2. Value added

According to the agency costs theory (Jensen and Meckling, 1976), a close supervision (i.e. monitoring) of portfolio firms after the investment event (Admati and Pfleiderer, 1994; Lerner, 1995) helps VC managers in: i) detecting potential problems (Mitchell et al., 1997); ii) reducing agency costs; and iii) increasing portfolio firm performance.

But agency costs theory neglects to consider that VCs perform a key coaching function (Colombo and Grilli, 2010), largely beyond pure monitoring. VC involvement allows the portfolio firm to increase the bundle of resources (Barney, 1991) it already had, including both financial (Hellmann and Puri, 2002) and managerial resources (Sørensen, 2007). During the holding period VCs provide help in defining strategic planning, assistance in management recruitment and compensation, access to their network of contacts (i.e. banks, suppliers and customers) and expertise in operational planning (Gompers and Lerner, 1998; Gorman and Sahlman, 1989; Sahlman, 1990; Sapienza et al., 1996; Sørensen, 2007), all of which become valuable resources for the portfolio firm (Shepherd et al., 2000). Such value-adding services are especially desirable in: i) early stage firms (Aspelund et al., 2005; Gerstein and Reisman, 1983); and ii) high-tech industries (Colombo and Grilli, 2005).

Hence, the resource-based view adds to the agency perspective by recognizing that access to resources and capabilities is an important driver of firm performance (Ireland et al., 2003). This complementary approach of agency costs theory and resource-based view is not new in the VC/private equity literature (Meuleman et al., 2009).

After accounting for the effect of funding, VC involvement should lead to an increase in firm performance grounded on better resources (i.e. value-adding services) and monitoring (e.g. incentives to portfolio firm's managers). Therefore, we posit the following hypothesis.

Hypothesis 2. The productivity growth of VC-backed firms is significantly higher than that of non-VC-backed ones in the holding period.

As suggested by Bamford et al. (1999) and Boeker (1989), early decisions and founding conditions 'imprint' the firm's future evolution. In these initial stages, entrepreneurs adopt an initial strategy based on the resources they have at hand and those they can realistically acquire (Dollinger, 1995). Since VC involvement implies a sort of 'firm re-birth', the resources provided by VCs contribute to the existing bundle of resources and help entrepreneurs in defining a new firm strategic behavior with long-lasting effects. Consequently, we expect that the 'imprinting' exerted by VCs during the holding period will continue to operate and benefit the portfolio firm, even after VCs' exit. The basic argument is that VCs' capabilities indelibly influence the organization and all sort of operations. In so doing the ways they organize things become routines that will continue to be active and effective even after their eventual departure (Barringer et al., 2005; Boeker, 1988, 1989; Heirman and Clarysse, 2005; Packalen, 2007; Stinchcombe, 1965).

In particular we assume that, once the impact of VCs' involvement (which moves the portfolio firm's productivity towards higher levels than before VCs' entry) is absorbed, portfolio firms do not decrease their performance (i.e. productivity growth). Therefore, we posit the following hypothesis.

Hypothesis 3. The productivity growth of VC-backed firms is not expected to decrease after VCs' exit.

Then, we go a step beyond in analyzing the characteristics of value added provided by VCs. In fact, the intensity of the effect of VC on firm performance might be different according to the different time elapsed from the first VC round. We argue that the value-adding services provided by VCs should determine an increase in firm performance especially in the first years after VCs' entry. Milanov and Fernhaber (2009) affirm that the most sensitive years are the first three years since the firm is established. Since we assume that the entry of a VC investor will imply a sort of re-birth of the portfolio firm, the most significant effect should be found in the first two years following the year of the first VC round, i.e. three years from the portfolio firm's re-birth (Bertoni et al., 2011). Therefore, we posit the following hypothesis:

Hypothesis 4. The productivity growth of VC-backed firms is significantly higher than that of the non-VC-backed ones in the first two years after the first VC round.

4. Methodology

4.1. The empirical models

We use the following model to test our first three hypotheses (H1, H2 and H3, hereafter):

$$Prod\_growth = \alpha_0 + \mu_i + \beta x_{i,t} + \gamma_{pre} VC_{i,t}^{in} + \gamma_{after} VC_{i,t}^{after} + \varepsilon_{it} \tag{1}$$

where $Prod\_growth_{i,t}$ is one-year productivity growth of firm i in year t. Productivity growth represents either TFP growth or partial (capital or labor) productivity growth.[4] $x_{i,t}$ is a set of control variables. In particular, we include country dummies, industry dummies and year dummies which allow us to control for cross-sectional differences among countries, industries and across time, respectively.[5] We also include firm age. μ_i represents firm-fixed effects; they are included to control for unobserved heterogeneity at firm-level that may lead to a biased estimate of VC coefficients. ε_{it} is an i.i.d. error term. $VC_{i,t}^{pre}$ is a dummy variable that equals 1 for firm i receiving VC financing in the two years prior to the first VC round (i.e. from $t-2$ to t, with t representing the VC investment year), and 0 otherwise. $VC_{i,t}^{in}$ is a dummy that equals 1 for firm i receiving VC financing, starting from the following year after the VC investment until the end of the holding period (i.e. from $t+1$ until the VCs' exit year, with t representing the investment year), and 0 otherwise. $VC_{i,t}^{after}$ equals 1 for firm i that received VC financing for later years, i.e. after VCs' exit year, and 0 otherwise.

To test H1 we look at the coefficient of $VC_{i,t}^{pre}$, representing the screening activity performed by VCs. If the coefficient is not significant we may conclude that screening does not significantly determine the future outperformance of VC-backed firms.[6]

H2 aims at estimating the value-adding effect provided by VCs. To test this effect, net of the screening effect, we need to perform the following Wald test:

$$\gamma_{in} - \gamma_{pre} > 0. \tag{2}$$

Similarly for H3, we test the (alleged) imprinting effect (i.e. the persistence in firm performance after VCs' exit) by verifying whether the productivity growth after VCs' exit is not lower than that achieved before VCs' entry. We perform the following Wald test:

$$\gamma_{after} - \gamma_{pre} \geq 0. \tag{3}$$

[4] Details on the estimation of the dependent variables are provided in Section 4.2.

[5] As a robustness check, we also include firm size among control variables, as explained in Appendix D.

[6] It is worth noting that if the coefficient of $VC_{i,t}^{pre}$ is not statistically significant, we can only claim that VCs' screening activity based on firms' past performance does not impact on subsequent performance of VC-backed firms. In Section 7 we check for the robustness of our results when controlling for the 'potentially different' growth orientation between VC-backed and non-VC-backed firms before VC funding. We are grateful to an anonymous referee for this suggestion.

As regards H4, which explores the timing of the value-adding effect engendered by VCs on firm's productivity growth, we use the following regression framework (similar to that suggested by Chemmanur et al., 2011):

$$Prod\_growth_{it} = \alpha_0 + \mu_i + \beta x_{i,t} + \gamma_{pre} VC_{i,t}^{pre} + \gamma_{short} VC_{i,t}^{short} + \gamma_{long} VC_{i,t}^{long} + \varepsilon_{it} \quad (4)$$

where $VC_{i,t}^{short}$ is a dummy that equals 1 in the first two years following the first VC round (i.e. from $t+1$ to $t+2$, with t representing the investment year, as suggested by Bertoni et al., 2011), and $VC_{i,t}^{short}$ equals 1 for later years (i.e. from $t+3$ until the end of the observation period), and 0 otherwise.

The impact of VCs in the short and long term, net of the screening effect, can be obtained by performing the following Wald tests, respectively:

$$\gamma_{short} - \gamma_{pre} > 0 \quad (5)$$

$$\gamma_{long} - \gamma_{pre} > 0. \quad (6)$$

4.2. The dependent variables

We analyze both TFP growth and partial (labor and capital) productivity growth measures. TFP measures the residual growth in a firm's output not accounted for by the growth in inputs (namely labor and capital), given the production technology in place in the firm's industry.[7]

More specifically, to estimate TFP, we resort to the GMM-system (GMM-SYS) estimator developed by Blundell and Bond (2000).[8] In accordance with Van Biesebroeck (2007), we estimate TFP separately for each industry. Then, in the final step, the residuals of the production function are used to estimate firm's TFP growth.[9]

We estimate labor and capital productivity growth measures as the ratio between logarithms of sales and payroll expenses and the ratio between logarithms of sales and fixed assets, respectively.

One may argue that labor productivity growth is a better measure of performance than TFP growth, because the measurement of labor productivity does not require the measurement of capital. In fact, the measurement of capital is difficult due to quality heterogeneity and, therefore, the estimates of TFP, as well as capital productivity, heavily depend on how capital is measured. Nevertheless, partial productivity measures are also subject to important criticism. Unlike TFP, labor and capital productivities are only partial measures of firm productivity. In particular, even if there is no improvement in productive efficiency, labor and capital productivities increase when other production inputs are used more relative to labor and capital inputs, respectively. In other words, partial productivities are valid measures of firm efficiency only if the proportion of each productive input remains constant.

The use of productivity growth as an indicator of the performance of entrepreneurial firms operating in high-tech industries is well-established in different streams of literature: entrepreneurship (e.g. Colombo et al., 2009; Cowling, 2003; Harada, 2004), finance (e.g. Chemmanur et al., 2010, 2011; Maksimovich and Phillips, 2001, 2008; Schoar, 2002), economics (e.g. Aghion et al., 2009; Aitken and Harrison, 1999; Cingano and Schivardi, 2004; Colombo et al., 2011; Hall and Mairesse, 1995; Javorcik, 2004; McGuckin and Nguyen, 1995) and innovation (e.g. Grilli and Murtinu, 2012).[10]

4.3. The estimation methodology

Eqs. (1) and (4) can be estimated using different estimation techniques. First, we make use of an OLS estimation in which we considered firm-specific effects as equal among all firms. In OLS estimations we control for selection by using a matched sample (as described in Section 5.1) and by inserting the term $VC_{i,t}^{pre}$ that isolates productivity growth differences between VC-backed firms and non-VC-backed ones before the receipt of VC financing.

Second, to properly evaluate the value-adding effect of VCs, we also use to the two-step system generalized method of moments estimator (GMM-SYS, Arellano and Bover, 1995; Blundell and Bond, 1998) with finite-sample correction (Windmeijer, 2005). The use of GMM-SYS allows us to estimate the impact of VC by controlling for its endogenous nature. Thus, we estimate both Eqs. (1) and (4) through the use of GMM-SYS by excluding the term $VC_{i,t}^{pre}$ and by considering the VC variables as endogenous (i.e. instruments start from $t-2$). However, to avoid the use of a large number of instruments resulting in significant finite sample bias, and the possibility of measurement errors causing potential distortions in our estimates, the instrument set is restricted with moment conditions in the interval between $t-2$ and $t-3$ (see Bond, 2002; Roodman, 2009).

Moreover, we follow an approach inspired by Sørensen (2007), adding to the set of instruments of the GMM-SYS estimator an additional variable ($VC\_fundraising_{it}$), which reflects the availability of VC funds at time t in the country in which the focal entrepreneurial firm i operates. This variable represents a good instrument since it is correlated to VC variables,[11] but independent

[7] As explained by Colombo et al. (2009, p. 348): 'An increase in TFP may be the result of demand side effects, such as the greater ability of the firm to command a premium price for its products or to extend market coverage. Alternatively, an increase in TFP may be due to supply side effects, like those stemming from the use of better quality production inputs or from their efficient use (lower quantity and/or lower price)'.

[8] See Appendix A for details on this estimation methodology.

[9] As robustness check, we also resorted to the semi-parametric procedure proposed by Olley and Pakes (1996). The results are very similar to those that are discussed in Section 6. They are not reported in the text for the sake of concision but are available upon request from the authors.

[10] We refer to examples of applications in samples partially or totally constituted by young and/or small firms operating in high-tech industries.

[11] This positive relationship between $VC\_fundraising_{it}$ and VC variable is confirmed by the results shown in Table 10, Panel A that will be described in Section 7.

from the error terms of the model. This way, independently of firm's future productivity growth perspectives, the likelihood of obtaining VC is higher if the firm operates in a geographical area with an abundance of VC. However, the effect of VC on firm's productivity growth is independent of $VC\_fundraising_{it}$, and so it is a source of exogenous variation (in a similar vein, see also, Bottazzi et al., 2008; Chemmanur et al., 2011; Ivanov and Xie, 2010).

5. Data and descriptive statistics

5.1. Sample selection process

The sample we used in this study is extracted from the VICO dataset. It includes data on entrepreneurial firms operating in seven European countries (Belgium, Finland, France, Germany, Italy, Spain, and the United Kingdom). VICO dataset stores information on two strata of firms, VC-backed firms and non-VC-backed (but potentially investable) ones. All firms included in the VICO dataset were: i) less than 20 years old in 2010; ii) were independent at foundation (i.e. not controlled by other business organizations); and iii) operate in medium and high-tech manufacturing and services industries (see Table 2).[12]

Both the groups of VC-backed and non-VC-backed firms include surviving and non-surviving firms (i.e. firms that ceased operations or were acquired). Data were collected through a variety of commercial and proprietary sources. For VC-backed firms, data were first obtained from VentureXpert. More specifically, the VICO dataset includes all equity (or equity-like) financing provided by VCs to entrepreneurial firms in the early stages of their life (seed, early-stage, late-stage and expansion capital).[13] Then, other sources (e.g. investor annual reports, investor websites, press releases, VC association yearbooks in each of the seven European countries included in the VICO dataset, Zephyr) were used to improve the coverage of the dataset and cross-check the information. VC-backed firms that received their first round of investment after the tenth year since their foundation were not included. The VICO dataset includes VC-backed firms invested between 1994 and 2004. The main source for data on non-VC-backed firms was Amadeus. Other sources were also used to improve the coverage of the dataset (e.g. Creditreform in Germany, Italian business community's data bank in Italy).

We report a more detailed description of the VICO dataset in Appendix B.

The sample selection process we used in this analysis was based on several steps. First, for both VC and non-VC-backed firms, we constructed an unbalanced panel of firms whose data on input (labor costs and fixed assets value) and output (sales value) variables were available for at least five consecutive years. This strict requirement is a necessary condition since we lost one-year data in the GMM estimation of TFP (Blundell and Bond, 2000) because of first differences, and data on four consecutive years are required to test second-order serial correlation, as Arellano and Bond (1991) pointed out. This first step shrank our dataset to 359 VC-backed firms and 3956 non-VC-backed firms.

Second, we built a matched sample of non-VC-backed firms that is comparable to the sample of VC-backed firms according to a set of a priori defined characteristics (for a similar procedure in the VC literature, see e.g. Brau et al., 2004; Chemmanur et al., 2011; Engel and Keilbach, 2007; Jain and Kini, 1995; Megginson and Weiss, 1991; Puri and Zarutskie, forthcoming; Tian 2012). In fact, as we explained in Section 3.1, the receipt of VC financing cannot be plausibly interpreted as the result of a random process. Conversely, it is subject to a possible selection bias, i.e. firms choose whether or not to apply for VC funding and VCs select their portfolio firms from the pool of potentially investable firms. From an empirical point of view, the group of VC-backed firms may differ from that of non-VC-backed ones before the initial VC round. A matching estimator solves, at least partially, this selection bias. More specifically, we selected control group firms by using a propensity score method. The aim is to find, for each VC-backed firm that received VC financing in year *t*, pairs of non-VC-backed firms that in the same year *t* had the most similar probability (i.e. propensity score) of receiving VC. In particular, propensity scores are obtained by estimating, for each investment year, a probit model in which the dependent variable is the probability of receiving VC and the independent variables include firm age, firm size, country and industry dummies.[14] This second step shrank our dataset to 267 VC-backed firms and 429 non-VC-backed firms.

It is important to note that the matching procedure allows us to control for observed heterogeneity among treated and untreated firms, represented only by the characteristics included in the matching process. However, as discussed in the previous section, in order to properly evaluate the impact of VC financing, we resort to: i) a model specification that allows us to control for unobserved effects; and ii) a GMM estimation in order to control for the endogenous nature of VC.

5.2. Descriptive statistics

This study deals with a total matched sample of 696 firms, 267 of which are VC-backed. Matched firms are located in six European countries[15] and were established between 1984 and 2004.

[12] The sectors included in this study are those classified as "medium/high-tech sectors" according to the statistical classification of economic activities in the European community.

[13] The VICO dataset does not include information on LBO, real estate, distressed debt funds and other private equity investments that are not targeted to entrepreneurial firms operating in the industries shown in Table 2.

[14] We performed a nearest neighbor matching with Mahalanobis distance and selected two control observations for each treated firm. The sampling of the control group is performed with replacement so that each control group firm can be selected as a match for more than one VC-backed firm (possibly in different years). We also performed a sensitivity analysis by taking either one or three control firms for each treated unit in order to test the robustness of our results.

[15] Germany is not included due to lack of accounting information.

Table 2
Industry classification.

Sector	NACE rev.1	NACE rev.2
Pharmaceutical	24.4	21
ICT manufacturing	30.02 + 32 + 33	26
Robotics	29.5	28.99.20
Aerospace	35.5	30.30
TLC	64.2	61
Internet	72.60	63.11.30 + 63.12
Software	72.2	62
Web publishing		5.2
Biotech	73.1	72.11
Other	e.g. Energy, nanotech.	

For each firm in the sample, accounting data are available from their foundation (whenever possible) up to 2010 (or until available). Our sample includes 5257 firm–year observations (i.e. 7.55 yearly observations per firm).

The breakdown of our sample by country, industry[16] and foundation period is provided in Table 3.

Matched control group firms are distributed very similarly to VC-backed ones, as confirmed by Chi-squared tests ($\chi^2[5]=8.81$, $\chi^2[6]=3.52$ and $\chi^2[3]=3.92$ for country, industry and foundation period, respectively). This is not surprising, given that we included country dummies, industry dummies and age in the matching process. The effectiveness of our matching procedure is confirmed by looking at the composition of the control group before matching, in the last columns of Table 3. In fact, significant differences (at 1% significance level) are found between the control group as a whole (i.e. before matching) and the subsample of VC-backed firms, as confirmed by Chi-squared tests ($\chi^2[5]=832.15$, $\chi^2[6]=474.64$ and $\chi^2[3]=652.25$ for country, industry and foundation period, respectively).[17]

In Table 4, we report some descriptive statistics about size (in terms of total assets, fixed assets and sales), employment (in terms of payroll expenses and headcount) and age for VC-backed and matched non-VC-backed firms.

We show summary statistics, such as mean, median and number of observations for each category in both pre and post-investment periods.[18] Moreover, for every variable, we perform t-tests on the difference-in-mean between the group of VC-backed firms and the matched control group. With the exception of age,[19] we do not find significant differences between VC-backed firms and the matched control group before the initial VC round. Conversely, after the first VC round, VC-backed firms are, on average, larger than non-VC-backed firms in terms of total assets, sales, payroll expenses and headcount. This evidence seems to suggest a positive effect of VC on the growth of portfolio firms.

Table 5 shows descriptive statistics (such as mean, median and number of observations) on TFP and partial productivity growth of VC-backed firms against the matched control group, both in the years before and after the first VC round.

For all productivity growth measures we perform t-tests on the difference-in-mean between the VC-backed firms and the matched control group. No significant differences are found in the pre-investment period in terms of TFP growth and labor productivity growth. However, in the pre-investment period, VC-backed firms show a lower capital productivity growth than matched non-VC-backed firms (the difference is significant at 5% confidence level). Capital productivity is the measure of how well capital (both material and immaterial) is used in providing goods and services. For instance, a lower capital productivity growth could be related to firms that so far had not benefited, in terms of sales made, from the outcomes generated by their investments. This result becomes visible with the ability of VCs to pick firms possessing higher quality capital (e.g. patents) not already exploited and to support those firms in profiting from it.

VC-backed firms turn out to be more productive than matched non-VC-backed firms after the receipt of VC financing, in terms of both TFP growth and labor productivity growth. Moreover, the difference in capital productivity growth in the post-investment period is not significant. These unconditional summary statistics seem to suggest that VCs: i) do not show a significant performance in their screening activity (in terms of TFP and labor productivity growth); and ii) contribute to increasing firm's productivity growth.

6. Results

Table 6 reports the results of Eq. (1). The dependent variables are TFP growth (columns I and II), capital productivity growth (columns III and IV) and labor productivity growth (columns V and VI), respectively. Columns I, III and V refer to OLS estimations, whereas II, IV and VI report GMM estimations.

As regards H1, we find that VC-backed firms do not exhibit significantly different TFP and labor productivity growth to those of their matched counterparts before the first VC round, thus excluding a screening effect by VCs. In terms of capital productivity growth, we find a negative and statistically significant coefficient. This last result is in line with the descriptive statistics shown, as

[16] Note that we aggregate the previously displayed ten sectors (shown in Table 2) into seven macro-industries in order to have a sufficient number of observations in each industry to estimate our performance variable (TFP).
[17] See Appendix C for additional details on the sample used in this work.
[18] The divide between pre and post-investment periods for matched non-VC-backed ones is the year of inclusion in the matched sample.
[19] In terms of age, we find a statistically significant difference between VC-backed firms and the matched control group but this difference is small.

Table 3
Sample composition for VC-backed and non-VC-backed firms.

	VC-backed		Matched control group		Total control group	
	No. of firms	%	No. of firms	%	No. of firms	%
Country						
Belgium	14	5.24	28	6.53	265	6.70
Finland	30	11.24	41	9.56	475	12.01
France	64	23.97	117	27.27	1291	32.63
Italy	56	20.97	72	16.78	472	11.93
Spain	71	26.59	116	27.04	620	15.67
United Kingdom	32	11.99	55	12.82	833	21.06
Total	267		429		3956	
Industry						
Internet	51	19.10	74	17.25	444	11.22
TLC	18	6.74	24	5.59	182	4.60
Software	106	39.70	174	40.56	1769	44.72
ICT manufacturing	39	14.61	68	15.85	714	18.05
Biotech and pharmaceutical	32	11.99	55	12.82	317	8.01
Other high-tech manufacturing	10	3.75	19	4.43	251	6.34
Other high-tech services	11	4.12	15	3.50	279	7.05
Total	267		429		3956	
Foundation period						
1984–1989	12	4.49	29	6.76	733	18.53
1990–1994	47	17.60	70	16.32	842	21.28
1995–1999	113	42.32	183	42.66	1284	32.46
2000–2004	95	35.58	147	34.27	1097	27.73
Total	267		429		3956	

Note: Chi-squared tests on the differences between the matched control group and the subsample of VC-backed firms are the following: $\chi^2[5]=8.81$, $\chi^2[6]=3.52$ and $\chi^2[3]=3.92$ for country, industry and foundation period, respectively. Chi-squared tests on the differences between the control group as a whole and the subsample of VC-backed firms are the following: $\chi2[5]=832.15$, $\chi2[6]=474.64$, and $\chi2[3]=652.25$ for country, industry and foundation period, respectively.

preliminary evidence, in Table 5. This finding could be interpreted as if VCs were able to pick firms possessing higher quality capital (e.g. patents) not already exploited in terms of higher sales and allegedly help them in profiting from it. Therefore, European data on entrepreneurial firms in high-tech industries seem to reject H1 on the screening ability of VCs. This evidence differs from the findings of Chemmanur et al. (2011), which are based on a sample of American manufacturing firms.[20]

H2 and H3 focus on the impact of VCs on firm's productivity growth in the post-investment period. We estimate the value-adding effect engendered by VCs and the potential persistence of this effect on portfolio firms' productivity growth (even after VCs' exit). To properly evaluate the value added provided by VCs in OLS estimation, net of the screening effect, we resort to the Wald tests described in Section 4.1 and reported in the last rows of Table 6. TFP and capital productivity growth are significantly higher in VC-backed firms during the holding period. Moreover, portfolio firms do not exhibit a decrease in TFP, capital productivity and labor productivity growth measures after VCs' exit, thus suggesting an imprinting effect of VCs. In other words, portfolio firms are able to maintain the higher productivity level achieved during the holding period.

It is also worth noting that the effect of VC involvement seems to be persistent over time on capital productivity growth in OLS estimations (but not in GMM estimates). Either before or after VCs' exit, the capital productivity growth of VC-backed firms is significantly higher than that of the matched control group at 1% and 5% statistical significance levels. However, this result might be driven by a 'substitution effect' in input factors. In other words, VC endorsement could shift portfolio firms towards less capital-intensive production processes. Portfolio firms may use less capital with respect to labor, as roughly suggested in Table 4. Unfortunately, we cannot test this 'substitution effect' because we do not have data on materials, energy and fuel (for a similar exercise, see Hirukawa and Ueda, 2008).

Quite surprisingly, labor productivity growth in VC-backed firms is not significantly higher than that of matched non-VC-backed firms in the holding period. As explained before, this result might also be driven by a substitution effect in input factors. VCs might shift portfolio firms towards more labor-intensive production processes. In other words, portfolio firms may use more labor (e.g. in terms of higher salaries and wages) with respect to capital (see again Table 4). These results are consistent with the interpretation that VCs employ higher quality workers during their holding period in order to improve portfolio firms' operating efficiency, as previously documented by Hellmann and Puri (2002).

Tables 7, 8 and 9 allow us to test H4 by showing the results of Eq. (4). The dependent variables are TFP growth, capital productivity growth and labor productivity growth, respectively. In these models, the coefficients of VC^{short} and VC^{long} represent the impact of VCs in the short term and long term, respectively. As in Table 6, to evaluate the value added provided by VCs, net of the screening effect, in OLS estimation we resort to the Wald tests explained in Section 4.1. Each table reports both OLS and GMM estimations (columns I and II, respectively) on the full matched sample. In addition, with the purpose of completely excluding any selection effect, the third column of each table reports the results obtained performing GMM estimations on the subsample of VC-backed firms only.

[20] In addition to geographical factors, this discrepancy might be explained by the way in which the authors define the control group. They recognize that VC-backed firms are larger than non-VC-backed firms (see Table 2 in their paper).

Table 4
Descriptive statistics for VC-backed and matched non-VC-backed firms.

		Pre investment			Post investment		
		Control group	VC-backed firms	VC-backed vs Control group	Control group	VC-backed firms	VC-backed vs Control group
Total assets	Mean	3693.34	4036.06	342.72	6248.15	9000.56	2752.41**
	Median	453.83	1067.30		833.42	2908.94	
	Obs	1151	696		2999	1941	
Fixed assets	Mean	1621.42	945.26	−676.16	2306.97	2243.75	−63.22
	Median	61.02	183.63		106.77	464.18	
	Obs	1151	696		2999	1941	
Sales	Mean	3141.77	2820.15	−321.61	5159.34	6459.17	1299.83**
	Median	535.39	498.91		882.00	1887.00	
	Obs	1151	696		2999	1941	
Payroll expenses	Mean	820.51	1002.44	181.94	1685.34	2325.48	640.14**
	Median	185.54	292.55		347.11	1006.09	
	Obs	1151	696		2999	1941	
Headcount	Mean	22.61	24.31	1.70	41.10	50.90	9.80**
	Median	8.00	9.00		11.00	23.50	
	Obs	857	621		2459	1755	
Age	Mean	3.64	3.31	−0.33*	8.24	7.84	−0.40**
	Median	3.00	3.00		8.00	7.00	
	Obs	1151	696		2999	1941	

Data are expressed in thousand € and deflated by CPI (reference year: 2005).
** Represents statistical significance at 1%.
* Represents statistical significance at 5%.

In both OLS and GMM estimations our results on TFP growth are consistent with Chemmanur et al. (2011), who find that VC-backed firms exhibit a higher TFP growth in the first years after the initial VC round. However, Chemmanur et al. (2011) also find a statistically significant long term effect on TFP growth.

With regard to the two variables measuring partial productivity growth, there is a positive and significant effect on firm productivity growth in the short term, whatever the dependent variable used. We interpret the discrepancy in results on labor productivity growth obtained in estimating Eqs. (1) and (4) by assuming that the positive effect engendered by VCs is not related to its presence, although it acts in the first years after VCs' entry. We also find a positively significant impact on capital productivity growth from the third year after VCs' entry on at 1% confidence level both through OLS and GMM estimations on the subsample of VC-backed firms. This finding is in line with what we found in Eq. (1) through OLS.

Finally, as regards control variables, we find a negative coefficient of firm age (even though not always statistically significant) in all the estimates. This result is coherent with the extant empirical literature.

We ran several different checks to test the robustness of our findings. The results of these additional estimates are reported and discussed in Appendix D.

7. Further analyses

As explained in Section 3.1, we model VCs' screening as a process based on the 'current' economic performance of potentially investable entrepreneurial firms (for a similar approach see e.g. Chemmanur et al., 2011; Davila et al., 2003). Even though this idea is well grounded in both finance and entrepreneurship literature, VCs might select their portfolio firms through the assessment of their 'potential performance'. Moreover, firm's potential performance might be influenced by the environmental settings in which the focal firm operates (e.g. Clarysse et al., 2011).[21]

It is worth noting that in the VC literature (e.g. Kaplan and Lerner, 2010) the potential performance of portfolio firms is directly related to their market value at the time of VCs' exit (through IPO or trade sale). In this vein, our dependent variables are well suited to measure firm value. First, Chemmanur et al. (2011) show that productivity growth is positively related to the probability of IPO.[22] Second, Schoar (2002) suggests that productivity growth is linked to firm profits (and so to firm value).[23] To some extent, through the use of productivity growth we provide an indirect measure of firm value without incurring the well known disadvantages related to the direct measures of profitability (see Griffiths et al., 2011). Third, Hirukawa and Ueda (2008) claim that another proxy

[21] Gilbert et al. (2006) suggest that the potential performance of entrepreneurial firms is a function of the industry structure and geographic location, among others. With regard to the industry structure, the authors claim that the characteristics of the industry in which the entrepreneurial firm operates explain part of its growth pattern (see also Clarysse et al., 2011; Delmar et al., 2003; Katila and Shane, 2005; Mishina et al., 2004). With regard to the geographical location, the authors refer to the availability of key resources (e.g. human capital, skilled workers, workers with specific competences) that enable the focal entrepreneurial firm to pursue its growth strategy (see also Wan and Hoskisson, 2003). We control for the different environmental settings in which sample firms operate through the inclusion of industry and country dummies in our matching procedure.

[22] More specifically, Chemmanur et al. (2011) refer to TFP growth.

[23] This is well explained by Chemmanur et al. (2011, p. 4050): 'Holding input costs constant, a certain percentage increase in productivity translates to an equal percentage increase in revenues, ceteris paribus. An increase in revenues leads to a more than proportional increase in profits, since the elasticity of profits to productivity is greater than one. Intuitively, an increase in productivity when all else remains constant leads to higher revenues without changing costs. Since profits are revenues minus costs, the smaller the profit margin, the higher the elasticity of profits to productivity'.

Table 5
Descriptive statistics of productivity growth measures for VC-backed and matched non-VC-backed firms.

		Pre investment			Post investment		
		Control group	VC-backed	VC-backed vs control group	Control group	VC-backed	VC-backed vs control group
TFP growth	Mean	0.059	0.017	−0.041	0.021	0.104	0.083**
	Median	0.041	0.061		0.009	0.071	
	Obs	440	261		2759	1797	
Capital productivity growth	Mean	0.010	−0.049	−0.059*	0.039	0.043	0.004
	Median	0.020	−0.008		0.019	0.023	
	Obs	691	413		2858	1905	
Labor productivity growth	Mean	−0.034	−0.069	−0.036	−0.013	0.010	0.022**
	Median	−0.011	−0.019		−0.003	0.000	
	Obs	669	395		2906	1905	

** Represents statistical significance at 1%.
* Represents statistical significance at 5%.

of firm value is labor productivity growth. In fact, the latter measure is used by financial analysts to assess the portfolio firm's ability to generate cash flows in the years after VC funding.[24]

However, to remove any doubts about the reliability of our results, we try to control for the 'potentially different' growth orientation between VC-backed and matched non-VC-backed firms before VC funding.[25] We consider two common measures of growth orientation[26]: the ratio between intangible assets and total assets (e.g. Caves, 1982; Itami, 1987; Myers, 1977) and the number of employees (Chandler et al., 2009).

As regards the latter, Chandler et al. (2009, p. 375) claim that: 'For the managers of emerging ventures, hiring permanent employees may respond to opportunities to expand, gain market share, and provide employment'. Moreover, a growth in the number of employees is a signal that the 'venture is equipped with new human capital through which its objectives can be executed' (Gilbert et al., 2006). As shown in Table 4, we do not find significant differences between VC-backed firms and matched non-VC-backed firms before the initial VC round in term of number of employees. In other words, if the number of employees is a good proxy of firm's growth orientation, there are not statistically significant differences between VC-backed and matched non-VC-backed firms in terms of potential performance. This result seems to confirm the absence of a screening effect by VC in European entrepreneurial firms.

With regard to the first measure of growth orientation (i.e. the ratio between intangible assets and total assets), Mahoney and Pandian (1992, p. 370) suggest that 'intangible resources supply the genetics of firm heterogeneity'. To some extent, this measure seems to be tailored to capture significant differences in growth orientation between VC-backed and matched non-VC-backed ones before the first VC round. This argumentation is also confirmed by Itami (1987), who claimed that intangible assets are often the only source of competitive advantage that can be sustained over a long period.[27] If VCs select portfolio firms on the basis of their intangible assets, our results on value added provided by VCs to their portfolio firms might be misleading. Thus, to isolate the effect of VC value added from VC screening (allegedly or at least partially based on growth orientation), we employ a switching regression-type methodology with endogenous switching.[28] In the first stage, we run a probit model to predict the likelihood of getting VC funding and we obtain the inverse Mills ratios for VC-backed and matched non-VC-backed firms. Among the covariates, we include the ratio between intangible assets and total assets, firm age, the annual VC fundraising in the country in which the focal entrepreneurial firm operates (see Section 4.3), the average TFP level in the two years before VC funding (or before the inclusion in the matching procedure for matched non-VC-backed firms), country dummies, industry dummies and year dummies. In the second stage, we run two separate OLS regressions for VC-backed and matched non-VC-backed firms, respectively. The dependent variables are represented by TFP growth. The covariates include the inverse Mills ratios estimated in the first stage (to account for the endogenous nature of VC screening based on unobservable factors) and all of the covariates included in the first stage with the exclusion of VC fundraising.[29] The predicted values of TFP growth are used to answer to the following questions: i) what would the TFP growth of a VC-backed firm have been had it not received VC funding?; and ii) what would the TFP growth of a matched non-VC-backed firm have been had it received VC funding?

Panel A of Table 10 reports the results of our analysis. In the first stage (column I), firm age has a positive impact on the likelihood of getting VC funding. As regards the exclusion restriction, the coefficient of VC fundraising is positive and significant. With regard to the variables of interest, prior average TFP is not significant in predicting VC backing, thus confirming our results on H1, about screening ability based on past productivity growth. Conversely, the ratio between intangible assets and total assets is positive and significant, thus casting some doubts about our results on VC screening based

[24] In Appendix D, we employ another measure linked to portfolio firm value: the logarithm of sales. Such performance measure is well grounded in both entrepreneurship (e.g. Chandler et al., 2009; Delmar, 1997; Wiklund and Shepherd, 2003a,b) and VC literature (e.g. Puri and Zarutskie, 2012). The results are in line with those based on productivity growth measures, reassuring us about the goodness of our main dependent variables.

[25] We are grateful to an anonymous referee for this suggestion.

[26] In many studies growth orientation is called growth potential or growth opportunity. Henceforth, we use the term growth orientation.

[27] This may be especially true for entrepreneurial firms, as 'their growth performance is closely related to unobservable characteristics such as a brilliant business ideas, the development of a unique technology, or a team of smart owner-managers' (Bertoni et al., 2011).

[28] This methodology is not new in VC literature (e.g. Chemmanur et al., 2011; Colombo and Grilli, 2010; Jelic et al., 2005; Lee and Wahal, 2004).

[29] We use VC fundraising as an exclusion restriction variable as customary in this type of models. For more details, see Heckman (1979) and Maddala (1983).

Table 6
Impact of VC on firm's productivity growth. Screening and value-adding effects. Estimates of Eq. (1). The dependent variables are TFP growth estimated through Blundell and Bond (2000) methodology (columns I and II), capital productivity growth (columns III and IV) and labor productivity growth (columns V and VI). Country, industry and year dummies are included in the estimates (coefficients are omitted in the table). As shown in Section 4.1, the estimates of VC impact are in the last rows of the table. Estimates are derived from OLS regressions with robust clustered standard errors and GMM estimations. Standard errors in round brackets. Degrees of freedom in square brackets.

	Coefficient	TFP growth		Capital productivity growth		Labor productivity growth	
		OLS	GMM	OLS	GMM	OLS	GMM
$VC_{i,t}^{pre}$	γ_{pre}	−0.059		−0.101**		−0.062	
		(0.057)		(0.037)		(0.040)	
$VC_{i,t}^{in}$	γ_{in}	0.093**	0.119**	0.010	0.079*	0.016*	0.032
		(0.021)	(0.045)	(0.014)	(0.034)	(0.006)	(0.016)
$VC_{i,t}^{after}$	γ_{after}	0.063	−0.101	−0.004	−0.004	0.017*	−0.020
		(0.039)	(0.150)	(0.017)	(0.034)	(0.009)	(0.041)
Age		−0.012**	−0.013**	0.002	0.003	−0.001	0.000
		(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)
Cons.		0.068	0.018	−0.405	0.022	0.001	−0.055
		(0.195)	(0.068)	(0.391)	(0.048)	(0.034)	(0.039)
Year dummies		Yes	Yes	Yes	Yes	Yes	Yes
Country dummies		Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies		Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.		4976	4560	4857	4448	4889	4474
No. of firms		657	657	654	654	655	655
Hansen stat.			51.745 [2]		38.710 [52]		57.256[2]
AR1			−5.832**		−3.744**		−3.053**
AR2			−0.053		1.667		0.615
Holding period effect	$\gamma_{in}-\gamma_{pre}$	0.152*		0.111**		0.078	
		(0.061)		(0.036)		(0.041)	
After VC exit effect	$\gamma_{after}-\gamma_{pre}$	0.122		0.097*		0.079	
		(0.070)		(0.038)		(0.041)	

** Indicate significance level at 1%.
* Indicate significance levels at 5%.

on growth opportunities. However, when we look at second stage results (columns II and III), we see that the inverse Mills ratios calculated in the first stage are positive and statistically significant in both equations. These findings reassure us about the reliability of our results on screening shown in Section 6. In fact, in the event of a positive effect of VC screening on

Table 7
Impact of VC on firm's TFP growth. Short and long term effects. Estimates of Eq. (4). The dependent variable is TFP growth. Country, industry and year dummies are included in the estimates (coefficients are omitted in the table). As shown in Section 4.1, the estimates of VC impact are in the last rows of the table. OLS and GMM I columns refer to the estimations based on the full matched sample, including both VC and matched non-VC-backed firms. GMM II column refers to the estimations based on VC-backed firms only. Estimates are derived from OLS regressions with robust clustered standard errors and GMM methods. Standard errors in round brackets. Degrees of freedom in square brackets.

	Coeff.	OLS	GMM I	GMM II
VC^{pre}	γ_{pre}	−0.042		
		(0.051)		
VC^{short}	γ_{short}	0.196**	0.227**	0.333*
		(0.051)	(0.075)	(0.131)
VC^{long}	γ_{long}	0.055**	0.015	0.149
		(0.021)	(0.046)	(0.106)
Age		−0.012**	−0.012**	−0.015**
		(0.002)	(0.002)	(0.004)
Cons.		0.106	0.038	−0.068
		(0.192)	(0.069)	(0.128)
Year dummies		Yes	Yes	Yes
Country dummies		Yes	Yes	Yes
Industry dummies		Yes	Yes	Yes
No. of obs.		5257	4820	1888
No. of firms		696	696	267
Hansen stat.			58.192 [52]	54.233 [52]
AR1			−5.253**	−3.356**
AR2			0.114	0.240
Short run effect	$\gamma_{short}-\gamma_{pre}$	0.238**		
		(0.074)		
Long run effect	$\gamma_{long}-\gamma_{pre}$	0.097		
		(0.053)		

** Indicate significance level at 1%.
* Indicate significance levels at 5%.

Table 8
Impact of VC on firm's capital productivity growth. Short and long term effects. Estimates of Eq. (4). The dependent variable is capital productivity growth. Country, industry and year dummies are included in the estimates (coefficients are omitted in the table). As shown in Section 4.1, the estimates of VC impact are in the last rows of the table. OLS and GMM I columns refer to the estimations based on the full matched sample, including both VC and matched non-VC-backed firms. GMM II column refers to the estimations based on VC-backed firms only. Estimates are derived from OLS regressions with robust clustered standard errors and GMM methods. Standard errors in round brackets. Degrees of freedom in square brackets.

	Coeff.	OLS	GMM I	GMM II
VC^{pre}	γ_{pre}	−0.104**		
		(0.033)		
VC^{short}	γ_{short}	0.015	0.049*	0.194**
		(0.018)	(0.022)	(0.046)
VC^{long}	γ_{long}	0.001	0.049	0.220**
		(0.015)	(0.035)	(0.066)
Age		0.002	0.002	−0.004*
		(0.002)	(0.002)	(0.002)
Cons.		−0.375	0.024	−0.116
		(0.374)	(0.044)	(0.066)
Year dummies		Yes	Yes	Yes
Country dummies		Yes	Yes	Yes
Industry dummies		Yes	Yes	Yes
No. of obs.		5138	4708	1873
No. of firms		693	693	267
Hansen stat.			57.506 [54]	54.608 [54]
AR1			−3.837**	−5.580**
AR2			1.669	−0.293
Short run effect	$\gamma_{short} - \gamma_{pre}$	0.119**		
		(0.033)		
Long run effect	$\gamma_{long} - \gamma_{pre}$	0.105**		
		(0.034)		

** Indicate significance level at 1%.
* Indicate significance levels at 5%.

subsequent TFP growth of VC-backed firms, we would expect a positive and statistically significant coefficient in the regression for VC-backed firms but a non-statistically significant coefficient in the regression for matched non-VC-backed firms. Conversely, we can safely claim that in our sample there is not a VC screening that positively affects the future TFP growth of

Table 9
Impact of VC on firm's labor productivity growth. Short and long term effects. Estimates of Eq. (4). The dependent variable is labor productivity growth. Country, industry and year dummies are included in the estimates (coefficients are omitted in the table). As shown in Section 4.1, the estimates of VC impact are in the last rows of the table. OLS and GMM I columns refer to the estimations based on the full matched sample, including both VC and matched non-VC-backed firms. GMM II column refers to the estimations based on VC-backed firms only. Estimates are derived from OLS regressions with robust clustered standard errors and GMM methods. Standard errors in round brackets. Degrees of freedom in square brackets.

	Coeff.	OLS	GMM I	GMM II
VC^{pre}	γ_{pre}	−0.049		
		(0.034)		
VC^{short}	γ_{short}	0.050**	0.070**	0.115**
		(0.017)	(0.024)	(0.040)
VC^{long}	γ_{long}	0.008	0.006	0.056
		(0.008)	(0.016)	(0.038)
Age		−0.001	−0.000	−0.001
		(0.001)	(0.001)	(0.001)
Cons.		0.068	−0.050	−0.135
		(0.054)	(0.039)	(0.097)
Year dummies		Yes	Yes	Yes
Country dummies		Yes	Yes	Yes
Industry dummies		Yes	Yes	Yes
No. of obs.		5170	4734	1872
No. of firms		695	694	267
Hansen stat.			56.669 [53]	56.907 [53]
AR1			−3.274**	−1.892*
AR2			0.839	−0.684
Short run effect	$\gamma_{short} - \gamma_{pre}$	0.099**		
		(0.037)		
Long run effect	$\gamma_{long} - \gamma_{pre}$	0.057		
		(0.036)		

** Indicate significance level at 1%.
* Indicate significance levels at 5%.

Table 10
The dependent variables are the likelihood to get VC funding (column I) and TFP growth estimated through Blundell and Bond (2000) methodology (columns II and III). Country, industry and year dummies are included in the estimates (coefficients are omitted in the table). Estimates are derived from probit and OLS regressions with robust clustered standard errors. Standard errors in round brackets.

	First stage	Second stage	
	Dependent variable: VC backing dummy	Dependent variable: TFP growth	
		VC-backed firms	Non-VC-backed firms
Panel A. Switching regressions with endogenous switching for VC-backed and matched non-VC-backed firms.			
Average two years prior TFP	−0.2846	0.2708*	0.2474**
	(0.2375)	(0.1217)	(0.0726)
Intangible on total assets	1.1703**	−0.5386	0.0487
	(0.3792)	(0.3051)	(0.2288)
Age	0.0294**	−0.0254	−0.0104
	(0.0202)	(0.0158)	(0.0061)
VC_fundraising	0.0000**		
	(0.0000)		
Inverse Mills ratio		0.6781**	0.5396**
		(0.2145)	(0.1477)
Cons.	−1.5154**	0.9289	−0.0138
	(0.3991)	(0.9248)	(0.0817)
Year dummies	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
No. of obs.	2236	862	1374
No. of firms	269	98	171
Panel B. Actual and hypothetical TFP growth for VC-backed firms and matched non-VC-backed firms.			
	Actual TFP growth for VC-backed firms	TFP growth for VC-backed firms if they had not obtained VC financing	TFP growth improvement
Mean	.0337	−0.3995	0.4332**
	Actual TFP growth for non-VC-backed firms	TFP growth for non VC-backed firms if they had obtained VC financing	TFP growth deterioration
Mean	0.0240	0.9371	−0.9131**

** Indicate significance level at 1%.
* Indicate significance levels at 5%.

VC-backed firms. More interestingly, the ratio between intangible assets and total assets is not significant in both second stage equations. So, it seems that the higher TFP growth of VC-backed firms than that of matched non-VC-backed firms is not driven by their different growth orientation.

In Panel B of Table 10, we answer the two abovementioned questions in order to test whether our results on value added hold. VC-backed firms show a TFP growth 43.32% higher than what the same firms would have shown had they not received VC funding. Similarly, matched non-VC-backed firms show a decrease in TFP growth of 91.31% than what the same firms would have shown had they received VC funding. To sum up, after controlling for the potential reliance of VCs' screening on proxies of firm's growth orientation, we can safely say that our results seem to be confirmed. First, there is a value-adding effect of VCs on TFP growth of their portfolio firms. Second, there is not a screening effect that positively affects the future TFP growth of VC-backed firms. This latter finding is reinforced by the fact that the TFP growth improvement of VC-backed firms is lower than the absolute value of TFP growth deterioration of matched non-VC-backed firms.

Finally, we test whether our results on VCs' screening change by controlling for the reputation of the VC investor. As highlighted by Bygrave and Timmons (1992, p. 208): ‘It is far more important whose money you get than how much you get or how much you pay for it’. For each VC investor we computed two different reputation measures widely used in the literature (Balboa and Martí, 2007; Tian, 2012, among others): i) total assets under management; and ii) the cumulative number of investments. Both measures are calculated at the time of VC investment in the focal portfolio firm (source: VentureXpert). More specifically, for each reputation measure we calculated the median value that acts as threshold between high-reputation VCs and low-reputation VCs. For each reputation measure, we performed a *t*-test in which the null hypothesis is the equality between high-reputation VC-backed firms and low-reputation VC-backed ones in the average level of portfolio firm's TFP in the two years before VC funding. Neither of the *t*-tests rejects the null hypothesis: Prob $(|T|>|t|)=0.5431$ and Prob $(|T|>|t|)=0.2644$ for the total assets under management and the cumulative number of investments, respectively). This result allows us to exclude a different screening ability among VCs with different reputation.

8. Discussion and conclusions

The analysis of the impact of VC financing on the performance of European entrepreneurial firms is important for managers, VCs and government authorities. There are many empirical papers that have shown the superior performance of VC-backed firms after the first VC round. Nevertheless, since it is well documented that VC managers follow a very well-structured screening process, critics have often pointed out that portfolio firms perform better because they were actually better before the investment.

We proposed a procedure that allows us to control for such reverse causality concerns and furthermore that allows isolating the 'value added' effect from the purely 'financial' effect. First, our results show that productivity growth is not significantly higher in VC-backed firms than matched non-VC-backed firms before the first VC round. This is not in line with some previous studies, mostly based on US manufacturing firms. Such studies provide evidence of the strong screening abilities of US VCs. This difference in screening abilities between US and European VCs might be explained by the higher level of development of US VC market (than that of the European VC market) in financing entrepreneurial firms (e.g. Hege et al., 2003). We also test whether our results on screening were not driven by either different growth orientation between VC-backed firms and matched non-VC-backed ones or the reputation of VCs.

Secondly, we show that productivity growth is substantially higher in VC-backed firms than in matched non-VC-backed ones after the first VC round. Moreover we find an 'imprinting' effect of VC as portfolio firms' productivity growth does not decrease after VCs' exit. Finally, we find that the impact of value-adding services provided by VCs is higher in the first two years after the first VC round.

This paper contributes to the extant VC literature in several ways. First, to the best of our knowledge, it is the first large-scale multi-country empirical study in Europe on the impact of VC financing on entrepreneurial firms' performance in high-tech industries. Second, we address the reverse causality issue that arises from the idea that it is 'screening' rather than 'value added' that drives the superior performance of VC-backed firms. Third, we suggest productivity growth measures as a way to distinguish between financial support and non-financial value added provided by VCs and provide evidence on the importance of the latter as the main driver of the better performance of VC-backed firms. Fourth, it is the first study in VC literature aimed at investigating the presence of an "imprinting effect" of VCs on firm performance. Finally, most previous studies in this field suffer from methodological weaknesses, which are solved in our work.[30]

We are aware that this study has some limitations, which open up opportunities for future research. First, we focus on six European countries. This raises the issue of whether our results could be extended to other European countries. In particular, the VC market in Europe is not as mature as in the US. Therefore, having access to VC is probably more important (even though more difficult) for European entrepreneurial firms than for their US counterparts. Moreover, VCs' screening abilities might be more effective in the US because they have more experience. As suggested by Hege et al. (2003, p.4): 'venture capital firms in Europe […] seem to be still lagging in their capacity to select projects. […] US VCs have better screening skills (due to their greater experience) than European ones. It follows that US VCs are better at sorting out good projects from bad ones'. This might also explain the differences found in our results, when compared to those based on US data (e.g. Chemmanur et al., 2011). Thus, it could be very useful in future works to compare US and European VC industries to understand the peculiarities as well as the features Europe has in common with the United States. Second, it would be interesting to analyze whether the support provided by different types of VCs (e.g. independent, corporate, and governmental) differs significantly. In fact, VCs constitute a quite heterogeneous crowd, especially in Europe where non-traditional VCs play an eminent role (Bottazzi et al., 2004; Tykvova, 2006). Indeed, we expect that the effect of VC financing should differ according to the identity of the investor (Tykvova and Walz, 2007; Grilli and Murtinu, 2011, 2012). Third, even though the use of productivity growth is a strength in this work, it would be interesting to go a step further and examine what precisely are the sources of the positive effect of VC endorsement on the productivity growth of European entrepreneurial firms, i.e. whether it is mainly an output side (revenue growth) or an input side (cost saving) effect. Fourth, future research should be able to test the 'substitution effect' in production inputs as we suggested in Section 6. Unfortunately, we do not have data to test that idea. It would also be interesting to check whether the potential 'substitution effect' is related to country-specific and/or industry-specific characteristics (e.g. the potential size of the labor force, the value of R&D investment). Finally, it is worth noting that, as in almost all of the extant literature, we do not have information on other types of financing than VC (e.g. business angels, public funds, other types of pre-seed funding). This important issue, which goes beyond the scope of our work, deserves a careful evaluation in future research.

In spite of the above limitations, this study considerably extends our understanding of the impact of VC investments on the performance of European entrepreneurial firms in high-tech industries. From a policy perspective, this study reveals that VC financing is a valid tool for improving the performance of European entrepreneurial firms and indirectly to increase the dynamic efficiency of the economic system. Since the business environment in Europe makes it difficult for VCs to successfully develop and exit entrepreneurial firms, incentive schemes should be further developed to enhance this type of investment (for a review of the European policy initiatives in recent years, see Bertoni and Croce, 2011).

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[30] First, some of these studies focus on IPO firms only, the reason being that information about these firms is easier to collect. However, focusing on samples composed only of IPO firms may create biases with respect to the outcome of the investment, the type of investor, the type of firm, and the sectors which are represented in the sample. Moreover, the analysis of firm performance in the period following the IPO does not allow disentangling the effect of VC financing from that of the IPO. Second, many studies include only a population of firms which survived as independent firms up to a certain date. This gives rise to survivorship bias due to lack of control for bankruptcy and mergers and acquisitions. Third, many studies addressing the impact of VCs on different aspects of performance suffer from a lack of a proper control for the counterfactual and for the potential endogeneity of VC financing.

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Appendix A. TFP estimation

To estimate TFP, we use the GMM-system (GMM-SYS) estimator developed by Blundell and Bond (2000). We assume a Cobb–Douglas production function. Mairesse and Hall (1996) show that the use of GMM-difference (hereafter, GMM-DIF) (Arellano and Bond, 1991) to estimate Cobb–Douglas production functions produces biased estimates, leading to a downward-bias in the estimation of the coefficient of capital. Moreover, returns to scale are greatly decreasing. This is due to the fact that GMM-DIF relies on first-differenced equations of the production function. But the series of inputs (capital and labor) and output (sales) are highly persistent and thus their lags represent weak instruments for the first-differenced equation (Blundell and Bond, 1998).[31] Blundell and Bond (2000) suggest that these problems are related to the weak correlations that exist between the current growth rates of firm output, capital and employment, and the lagged levels of these variables. GMM-SYS (Arellano and Bover, 1995) alleviates the typical problem of weak instruments characterizing the GMM-DIF estimator. In fact, it also uses the first differences of the inputs as instruments for the level equation.

Blundell and Bond (2000) show the importance of modeling a first-order autoregressive component in the error term of the production function. The residuals of the production function also include a fixed effect and the common i.i.d. component capturing potential transitory productivity shocks and measurement errors. In accordance with Blundell and Bond (2000), we employ this model:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \gamma_t + \eta_i + v_{it} + \zeta_{it} \tag{A.1}$$

where

$$v_{it} = \rho v_{it-1} + \varepsilon_{it} \tag{A.2}$$

and y_{it} is the logarithm of the sales of firm i at time t; k_{it} is the logarithm of fixed assets (tangible and intangible assets) of firm i at time t[32]; l_{it} is the logarithm of payroll expenses of firm i at time t[33]; γ_t is a vector of year dummies; $\eta_i + v_{it} + \zeta_{it}$ represents the composite error, given by the sum of a firm-specific unobserved effect, a first-order autoregressive productivity shock and the usual i.i.d. component, respectively. Consistent OLS estimates of the coefficients of the input factors in the Eq. (A.1) are prevented by a simultaneity problem. In fact, firms choose the input knowing their own level of productivity, leading to a correlation between regressors and the composite error term. Thus, we assume that capital and labor can be correlated with the composite error and we treat them as endogenous.

In the Eq. (A.2), ρ must be lower than one to ensure stationary assumptions of the model. To estimate the coefficients of capital and labor, we follow Blundell and Bond (2000). Thus, our lagged instruments start from $t-3$.

$$y_{it} = \rho y_{it-1} + \beta_l l_{it} - \rho\beta_l l_{it-1} + \beta_k k_{it} - \rho\beta_k k_{it-1} + \gamma_t - \rho\gamma_{t-1} + \eta_i(1-\rho) + \varepsilon_{it} + \zeta_{it} - \rho\zeta_{it-1}. \tag{A.3}$$

This is due to the fact that, in the dynamic representation of the model in Eq. (A.3), sales, capital and labor at time t may be correlated with productivity shocks in the periods t, $t-1$ and $t-2$. Thus, level instruments from the period $t-3$ are valid, i.e. they are orthogonal to the error term, under standard exogeneity assumptions on the initial conditions. To estimate the coefficients of capital and labor, we have to impose two non-linear restrictions: i) the coefficient of capital at the period $t-1$ must be equal to the product (with the opposite sign) of the coefficient of capital at time t and the autoregressive component; and ii) the coefficient of labor at the period $t-1$ must be equal to the product (with the opposite sign) of the coefficient of labor at time t and the autoregressive component. These restrictions must be tested and imposed through a minimum distance criterion.[34]

Appendix B. The VICO dataset

The VICO dataset has been built thanks to the joint effort of nine universities throughout Europe (Ecole des Mines de Paris, Politecnico di Milano, Libera Università Carlo Cattaneo, Research Institute of the Finnish Economy, Centre for European Economic Research (ZEW), Universidad Complutense de Madrid, University College London, Vlerick Leuven Management School, and University of Gent) with the

[31] Blundell and Bond (1998) claim that 'weak instruments could cause large finite sample biases when using the first-differenced GMM procedure to estimate autoregressive models for moderately persistent series from moderately short panels'.

[32] Unfortunately, we cannot control for the age of capital. As suggested by Hirukawa and Ueda (2008, p. 14): "Age of capital may affect TFP growth through either mis-measurement of capital and learning cost associated with introduction of new capital investments. When new equipment is introduced, its quality tends to be higher than that of old equipment. Nevertheless, the data may not be able to pick up this quality improvement and therefore may underestimate the amount of new equipment investment. As a consequence, we observe a faster TFP growth when new equipment investment is high and the age of capital declines (Nelson, 1964). Arguments that support the opposite relation also exist. Investment in new equipment entails the costs of learning it and therefore TFP growth may slow down following investment in new equipment (Greenwood and Yorukoglu, 1997). Whelan (2007) argues that introduction of new equipment causes overestimation of new equipment investment, contrary to Nelson's argument. When introduction of new equipment occurs, the relative price of new equipment against old equipment overstates the quality difference between old and new equipment. As a consequence, the new equipment investment may be overestimated".

[33] Measures of total assets, fixed assets, sales and payroll expenses are deflated by using CPI. Year 2005 is used as reference year. The source of CPI is the OECD Statistics.

[34] We use the STATA program md_ar1 to impose and test the validity of the common factor restrictions ex-post, based on a minimum distance procedure.

support of the 7th European Framework Program (Grant agreement no.: 217485). The objective of the data collection process was to build a large sample of entrepreneurial firms in order to provide a comprehensive picture of VC activity in high-tech sectors in seven European countries: Belgium, Finland, France, Germany, Italy, Spain and the United Kingdom.

All firms included in the sample were founded after 1984, were independent at foundation, and operate in the industries shown in Table 2. The dataset includes two strata of firms: the first includes a sample of VC-backed firms and the second a control group of non-VC-backed firms. All VC-backed firms received their first round of VC between 1994 and 2004 and were less than 10 years old at that time.

The data collection process was performed by eight teams, seven of which were responsible for gathering data on firms responding to the abovementioned criteria in the two strata, and one in charge of the central collection and construction of the overall dataset. Each local team started the identification of the VC-backed sample from a query on VentureXpert and then complemented the list by accessing other, often country-specific, sources such as: VC investor websites, local VC associations, press releases, press clippings, IPO prospectuses, stock exchange records, Zephyr, the Library House, the ZEW Foundation Panel, VCPro-Database, BVK Directory, the Research on Entrepreneurship in Advanced Technologies (RITA) directory, Private Equity Monitor, José Martí's VC Database, and webcapitalriesgo.com. The use of several sources of information allows the dataset to embrace a set of VCs which is usually largely underrepresented by more customary commercial data providers. Moreover, the sample includes both successful and non-successful deals and both surviving and non-surviving (e.g. bankrupt, acquired) firms.

The second stratum of the dataset is composed of non-VC-backed firms mainly deriving from a random extraction (conditional on the criteria reported above) from different calendar year versions of Bureau Van Dijk's Amadeus dataset and complemented by other country-specific sources such as: industry associations, Chambers of Commerce, commercial firm directories, Zephyr, Creditreform, the ZEW Foundation Panel, and the Research on Entrepreneurship in Advanced Technologies (RITA) directory. The extraction procedure of the control group ensures the inclusion of both surviving and non-surviving firms, to avoid the emergence of survivorship bias.

For each firm in the sample an in-depth information set was collected, including: general firm information (name, year of foundation, NACE rev. 1.1 and NACE rev. 2 industrial classifications, and NUTS2 geographic area), contact information (address, phone, fax, name and email address of a manager or founder), accounting information, patenting history (from European Patent Office), status (active, liquidated, acquired, inactive), and listing (if the firm went through an IPO and, if so, when). All VCs involved in firms in the VC-backed stratum across all stages were identified and information was collected about their experience, nationality and management typology. For each investor and round of financing, information was sought on: the date on which the investment occurred, the amount invested, the (fully-diluted) equity interest held, and the fund(s) (if any) which carried out the transaction. Finally, time and mode of exit (if any) by each investor in each VC-backed firm was also collected.

Information collected at local level was checked for reliability and internal consistency by each national team and regularly sent to the central data collection unit, which ensured that information was consistent and comparable across countries and its availability balanced; an increase in the target number of firms was requested when the information set in a country turned out to be sparser than average, to compensate for a higher expected loss of usable firm-year observations. Eventually, the dataset consists of 8370 firms, 759 of which are VC-backed. The breakdown by country, foundation period and industry is provided in Table A.1. For more details on the procedures used in the data gathering process and on all of the variables included in the dataset, see Bertoni and Martí (2011).

Table A.1
Composition of the VICO dataset by country, foundation period and industry.

	VC-backed firms	Control firms	Total
Country			
Belgium	89	826	915
Finland	68	692	760
France	112	1616	1728
Germany	134	1206	1340
Italy	98	959	1057
Spain	82	794	876
United Kingdom	176	1518	1694
Total	759	7611	8370
Foundation period			
1984–1989	22	1000	1022
1990–1994	92	1147	1239
1995–1999	339	2609	2948
2000–2004	306	2855	3161
Total	759	7611	8370
Industry			
Internet	134	842	976
Software	256	3502	3758
Telecommunications	44	343	387
ICT manufacturing	124	1380	1504
Biotech and pharma	159	706	865
Other high-tech manufacturing	23	437	460
Other R&D services	19	401	420
Total	759	7611	8370

Appendix C. Sample statistics

Table A.2 reports descriptive statistics on the number of VC-backed and matched non-VC-backed firms included in our sample both before and after the year of the initial VC investment.

Table A.2
Distribution of sample firms across the reference year.

	Years before and after the first VC round												
	−3	−2	−1	0	1	2	3	4	5	6	7	8	9
No. of VC-backed firms	68	99	158	267	259	257	253	251	228	195	159	131	88
No. of matched non-VC-backed firms	116	173	264	429	418	402	397	390	349	288	235	190	149
No. total firms	184	272	422	696	677	659	650	641	577	483	394	321	237

Note: As reference year we consider the year of first VC funding for VC-backed firms and the year of inclusion in matched sample for matched non-VC-backed ones.

In the case of matched non-VC-backed firms, the year in which the firm was included in the matching process is considered as reference year.[35] The number of firms included in our analysis is clearly equal to the number of firms available in the year of the first VC round, in accordance with our matching procedure. However, accounting data necessary to perform our analyses in the year before the first VC round are available only for 422 firms, 158 of which VC-backed. This number shrank to 272 firms, 99 of which VC-backed, if we look at two years before the investment. Similarly, the number of firms observed in the post investment period is decreasing over time.

Table A.3 provides details on the year of first VC round in our sample.

Table A.3
Descriptive statistics on the first VC round.

	Year of first VC round									
	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
No. of VC-backed firms	11	10	11	17	24	69	44	20	29	32
%	4.12	3.75	4.12	6.37	8.99	25.84	16.48	7.49	10.86	11.99

Descriptive statistics show that VC investments in our sample occurred between 1995 and 2004. The number of investments increases from 1995 until 2000, year in which it reaches its peak (69 investments out of 267). In 2001 and 2002 the number of VC investments dramatically falls to 44 and 20 respectively, and remains quite stable until the end of 2004.

For 228 out of the 267 VC-backed firms, the dataset includes information on VCs' exit. This information is compulsory to construct the variables $VC_{i,t}^{in}$ and $VC_{i,t}^{after}$ in Eq. (1).

Appendix D. Robustness checks

As robustness checks we run additional estimates of Eq. (4), only for TFP growth.[36] Results are reported in Table A.4.

First, a possible survivorship bias in our data may lead to misleading results. Firms exit our sample for two reasons: i) cease of operations; and ii) acquisition by another firm. Both of these events might be influenced by the presence of VC. Firm's survival rate might be influenced by its (potential) access to VC finance, either positively because VC-backed firms benefit from a larger endowment of financial and non-financial resources (Puri and Zarutskie, forthcoming), or negatively because they become more risk taking (Manigart and Van Hyfte, 1999). The presence of VC is also likely to influence the likelihood that firms are acquired, not least because trade sales are by far the most common way out for VC firms in Europe (Bottazzi et al., 2004). So, if there is a correlation (either way) between VC financing and exit and, in turn, exit was significantly correlated with productivity growth, our estimates would be biased. We thus implement a survivorship bias test in the spirit of Semykina and Wooldridge (2010). The procedure requires the estimation, for each year, of a selection equation for firm exit on the total VICO sample. The dependent variable in these probit models is $exit_{i,t}$, a dummy variable taking value 1 when firm i at time t exited the VICO sample. The independent variables include firm's total assets, firm age, the receipt of VC financing, industry and country dummies. We use the estimated coefficients from these selection models to compute the inverse Mill's ratio of survival for each firm–year observation included in the sample.[37] This time-varying

[35] If a matched non-VC-backed firm matches more than one VC-backed firm in different years, we consider the first year of inclusion in the matched control group as reference year.

[36] The estimates for capital and labor productivity growth and all the estimates of Eq. (1) are omitted in the text for the sake of concision but are available upon request from the authors.

[37] In our sample information on firm exit is available for 512 out of 696 firms, 201 of which VC-backed.

inverse Mill's ratio is then inserted as a control for survivorship bias in Eq. (4) which is then estimated both by OLS and GMM, respectively. Results are reported in Panel A of Table A.4 (Model I). The coefficient of the survivorship bias control is never significant thus excluding the presence of any remarkable survivorship bias in our sample.

Second, we include firm size as a control variable (Model II). In the estimation of firm productivity, we have already controlled for 'size effects' so, as is customary in this type of analysis (e.g. Colombo et al., 2011; Grilli and Murtinu, 2012), we do not include it in our baseline model. Nevertheless, as a check, we include it to control whether 'firm size effects' drive our results. As you can see in Panel A of Table A.4, the results of Model II are reported in columns III and IV (OLS and GMM estimations, respectively) and are in line with those presented and discussed in Section 6.

Third, in Panel B of Table A.4 we restrict our VC-backed sample to the 89 firms for which we have all required pre and post-investment observations (Model III) and compare them with the matched control group sample. The results of Model III in the first two columns (OLS and GMM estimations, respectively) are in line with those presented and discussed in Section 6.

Fourth, even though in Section 7 we explained the link between productivity growth measures and portfolio firm value, we re-estimate Eq. (4) with a different dependent variable: the logarithm of sales. In entrepreneurship literature, sales is the preferred measure of firm performance (e.g. Chandler et al., 2009; Delmar, 1997; Wiklund and Shepherd, 2003a,b). In the extant VC literature, many works test the impact of VC on such a measure (for a very detailed analysis, see Puri and Zarutskie, forthcoming). Hellmann and Puri (2000) show that one of the most important effects of VC backing is that VCs speed up the time to market of firms' products, thus leading the portfolio firm to the commercialization phase as soon as possible. This way, firm sales increase and this acts as a market signal that the firm's business is viable. Puri and Zarutskie (forthcoming) show that VC-backed firms achieve a higher level of sales than non-VC-backed firms. Moreover, firm age positively impact such difference in sales between VC and non-VC-backed firms. Estimates are reported in the last two columns in Panel B of Table A.4 (OLS and GMM, respectively). As you can see, our results suggest that VCs have a positive effect on firm sales. However, only the impact in the long term is statistically significant. Also in this case, we do not detect a screening effect of VCs. As in our results shown in Section 6, in OLS estimation we resort to the Wald tests explained in Section 4.1 to evaluate the value added provided by VCs, net of the screening effect. Our results are consistent with Chemmanur et al. (2011) and Puri and Zarutskie (forthcoming). However, Chemmanur et al. (2011) also find a statistically significant short term effect on sales.

Table A.4

Panel A. Robustness checks: Model I and II. Short and long term effects.

	Coeff	Model I — survivorship bias control		Model II — size control	
		OLS	GMM	OLS	GMM
VC^{pre}	γ_{pre}	−0.048		−0.062	
		(0.081)		(0.051)	
VC^{short}	γ_{short}	0.208**	0.266**	0.168**	0.188*
		(0.047)	(0.093)	(0.051)	(0.078)
VC^{long}	γ^{long}	0.078**	0.007	0.023	−0.030
		(0.025)	(0.092)	(0.022)	(0.052)
Age		−0.009**	−0.008**	−0.014**	−0.016**
		(0.002)	(0.002)	(0.002)	(0.002)
IMR		−1.368	0.141		
		(1.059)	(4.975)		
Size				0.024**	0.034**
				(0.006)	(0.011)
Cons.		−0.922	0.057	−0.045	−0.182
		(0.823)	(3.824)	(0.195)	(0.102)
Year dummies		Yes	Yes	Yes	Yes
Country dummies		Yes	Yes	Yes	Yes
Industry dummies		Yes	Yes	Yes	Yes
No. obs.		2954	2901	5257	4820
No. firms		512	512	696	696
Hansen stat.			34.548 [34]		57.001 [52]
AR1			−2.545*		−5.238**
AR2			0.876		0.139
Short run effect	$\gamma_{short} - \gamma_{pre}$	0.255**		0.230**	
		(0.095)		(0.074)	
Long run effect	$\gamma_{long} - \gamma_{pre}$	0.125		0.085	
		(0.082)		(0.053)	

Table A.4
Panel B. Robustness check: Model III and IV. Short and long term effects.

	Coeff	Model III — restricted sample of 89 VC backed firms		Model IV — dependent variable: logarithm of sales	
		OLS	GMM	OLS	GMM
VC^{pre}	γ_{pre}	−0.043		0.278	
		(0.055)		(0.173)	
VC^{short}	γ_{short}	0.121**	0.157**	0.309	0.312
		(0.043)	(0.058)	(0.136)	(0.132)
VC^{long}	γ_{long}	0.019	0.024	0.807**	0.627**
		(0.028)	(0.030)	(0.135)	(0.150)
Age		−0.01**	−0.011**	0.131**	0.139**
		(0.002)	(0.002)	(0.016)	(0.016)
Cons.		0.152	−0.021	7.164**	5.366**
		(0.116)	(0.062)	(0.476)	(0.435)
Year dummies		Yes	Yes	Yes	Yes
Country dummies		Yes	Yes	Yes	Yes
Industry dummies		Yes	Yes	Yes	Yes
No. obs.		4081	3749	5257	4820
No. firms		518	518	696	696
Hansen stat.			29.056 [49]		50.722 [53]
AR1			−5.350**		−1.758*
AR2			0.058		−1.112
Short run effect	$\gamma_{short}-\gamma_{pre}$	0.163*		0.031	
		(0.078)		(0.140)	
Long run effect	$\gamma_{long}-\gamma_{pre}$	0.062		0.529**	
		(0.056)		(0.173)	

The dependent variable is TFP growth. Country, industry and year dummies are included in the estimates (coefficients are omitted in the table). As shown in Section 4.1, the estimates of VC impact are in the last rows of the table. Estimates are derived from OLS regressions with robust clustered standard errors and MM methods. Standard errors in round brackets. Degrees of freedom in square brackets. ** and * indicate significance levels at 1% and 5%, respectively.

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