



Venture capital financing and the growth of high-tech start-ups: Disentangling treatment from selection effects

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ABSTRACT

The financial and innovation literature generally claims that venture capital (VC) investments spur the growth of new technology-based firms (NTBFs). However, it has proved difficult so far to separate the “treatment” effect of the VC investment from the “selection” effect attributable to the ability of the VC investor to screen high growth NTBFs. The aim of this work is to test whether VC investments have a positive treatment effect on the growth of employment and sales of NTBFs. For this purpose we consider a 10-year longitudinal data set for 538 Italian NTBFs, most of which are privately held. The sample includes both VC-backed and non-VC-backed firms. We estimate Gibrat-law-type dynamic panel-data models augmented with time-varying variables that capture the VC status of firms. To control for the endogeneity of VC investments we use several GMM estimators. The econometric results strongly support the view that VC investments positively influence firm growth. The treatment effect of VC investments is of large economic magnitude, especially on growth of employment. Most of it is obtained immediately after the first round of VC finance. Conversely, the selection effect of VC appears to be negligible in the Italian context.

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1. Introduction

It is widely recognized by scholars, practitioners and policy makers that new technology-based firms (NTBFs) play a crucial role for the static and dynamic efficiency of the economic system (Audretsch, 1995). In this area European countries lag behind their international competitors. In particular, high-tech entrepreneurial ventures which from the very beginning of their existence, experience high growth rates and eventually either become leaders in the industries in which they operate or even manage to create a new industry – companies like Intel, Microsoft, Google or Genentech, are quite rare in Europe while they abound in the US. To explain this difference governmental documents often mention the greater development of the venture capital (VC) sector in the US (see e.g. Revest and Sapio, forthcoming, and the early documents cited by Lockett et al., 2002).

There are several reasons why VC-backed NTBFs are likely to outperform their non-VC-backed counterparts (see e.g. Gompers and Lerner, 2001a,b; Denis, 2004). First, NTBFs are the firms most likely to be financially constrained (Carpenter and Petersen, 2002; Hall, 2002; Colombo and Grilli, 2007). Owing to superior scout-

ing capabilities (Chan, 1983; Amit et al., 1998), VC investors can identify firms with hidden value and provide them with the necessary financing. Second, VC investors actively monitor portfolio companies and perform a valuable coaching function (Gorman and Sahlman, 1989; Sapienza, 1992; Lerner, 1995; Sapienza et al., 1996; Kaplan and Strömberg, 2003, 2004). Third, VC investment is a “signal” of the quality of portfolio companies for uninformed third parties. VC-backed firms also benefit from the business contact network of VC investors. Hence, these firms have access to external resources and competencies that would be out of reach without the endorsement of a VC investor (Stuart et al., 1999; Colombo et al., 2006; Hsu, 2006; Lindsey, 2008).

Nonetheless, it has also been argued that the agency relation between VC investors and entrepreneurs may engender conflicts that are detrimental to portfolio firms (Ueda, 2004; Atanasov et al., 2006; Masulis and Nahata, 2009). First, VC investors may have objectives and strategies that are different from those of entrepreneurs. Second, VC finance might pose appropriability hazards for portfolio firms because VC investors might poach the innovative business ideas of entrepreneurs and exploit these themselves. Thus, it cannot be taken for granted that VC investments are beneficial to portfolio firms.

The aim of this work is to analyze the effect of VC investments on firm growth. We follow previous studies in considering growth as

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an indicator of the business success of NTBFs (Feeser and Willard, 1990; Fischer and Reuber, 2003; Barringer et al., 2005; Colombo and Grilli, 2005, 2010a). Even though it is quite difficult to find an unambiguous indicator of the performance of these firms, rapid growth generally signals wide market acceptance of their products or services. Moreover, growth is difficult to achieve and most high-tech start-ups remain small several years after their foundation. More precisely, we address the following research questions. First, do VC-backed firms enjoy higher growth than their non-VC-backed counterparts? Second, if this is the case, is this positive association mainly attributable to the ability of VC investors to select firms with future high growth prospects (i.e. to “pick winners”, Baum and Silverman, 2004) or is it a consequence of the (financial and non-financial) support they offer to portfolio firms (i.e. their ability to “build winners”)? In other words, do VC investments have a positive “treatment” effect on portfolio firms over and beyond the “selection” effect? Third, is the (allegedly positive) treatment effect of VC investments spread over time? Or does it occur immediately after the first round of VC finance?

To answer these questions, we empirically analyze the impact of VC investments on the growth of Italian NTBFs taking advantage of a 10-year (1994–2003) longitudinal data set for 538 start-ups in high-tech manufacturing and services sectors, 58 of which are VC-backed. We measure growth in both employees and sales. Our data set has several strengths in comparison with those used in previous studies. First, to the best of our knowledge this is the first study that uses a long longitudinal data set for both VC-backed and non-VC-backed firms, most (but not all) of which are privately held. Hence, our data set is not affected by the selection bias inherent in samples exclusively composed of IPO firms. In addition, as a consequence of the process used to build the sample (see Appendix A.1 for details), the dataset includes only NTBFs that are typical targets of VC investors. Conversely, lifestyle firms and other non-growth-oriented firms that would be very unlikely to be selected by VC investors are excluded from the data set. This yields more precise estimates of the relevant counterfactual (i.e. the growth rate VC-backed firms would experience if they were not VC-backed) than would be possible if we considered only VC-backed firms, or if low-tech firms and high-tech lifestyle firms, which clearly have different finance needs, were included in the sample. Second, data on VC investments were obtained from public sources (Italian Venture Capital and Private Equity Association, AIFI; and the financial reports of VC investors), from commercial databases (VentureXpert), and from a survey administered to NTBFs. Hence, coverage of VC investments, especially those made by small and medium industrial firms which generally are not covered by secondary sources, is more complete than in previous studies. Third, we implemented robust controls for the endogeneity of VC investments. The rather long observation period allowed the use of generalized method of moments (GMM) estimation techniques for panel data models. Moreover, our data set is very informative on sample firms since it includes detailed firm-, industry- and location-specific information. Hence, in testing the causality relation between VC investments and growth we included in the set of explanatory variables controls that account for selection based on observable variables and used a rich set of instruments for VC variables to control for selection based on unobservables. Fourth, in spite of the use of survey-based data, we controlled for possible survivorship bias, albeit in a partial way.

Our results clearly support the view that VC investments have a large positive effect on the growth of firm’s employment and sales that is not attributable to the ability of VC investors to select firms with superior growth prospects. In fact, the selection effect of VC investments is found to be negligible for Italian NTBFs. Quite interestingly, the treatment effect of VC investments on growth is larger

for employees than for sales, and it materializes almost immediately after the first round of VC finance regardless of which growth indicator is considered.

The remainder of the paper is structured as follows. In the next section we survey the literature on the effect of VC investments on firm growth. In Section 3 we provide some descriptive statistics for VC in Italy. In Section 4 we describe the sample of firms and analyze the pattern of VC investments among Italian NTBFs. In Section 5 we illustrate the econometric methodology and highlight the strengths and weaknesses of the different estimation techniques used in the paper. In Section 6 we present the econometric analysis results on the effect of VC investments on the growth of Italian NTBFs. In Section 7 we discuss the results, provide additional qualitative evidence on the nature of the treatment effect of VC investments and the matching process of VC investors and portfolio firms, acknowledge limitations and illustrate policy implications.

2. The effect of VC investments on firm growth: stylized facts and methodological weaknesses

Most studies that have analyzed the effects of VC investments on firm growth have relied on matched pair techniques or cross-sectional regressions to compare the growth rates of sales, employment or total assets of VC-backed and non-VC-backed firms (see e.g. Jain and Kini, 1995; Manigart and Van Hyfte, 1999; Audretsch and Lehmann, 2004; Alemany and Martí, 2005; Engel and Keilbach, 2007; Puri and Zarutskie, 2008). In general, a positive association between VC finance and growth is observed, although the results are not unanimous (see e.g. Bottazzi and Da Rin, 2002).

These studies suffer from serious methodological weaknesses. First, most of them only consider IPO firms. This engenders a serious sample selection bias. With IPOs generally being considered the most successful exit for VC investors, it is questionable whether results obtained for IPO firms can be generalized to privately held firms. Moreover, comparison of the growth of VC-backed and non-VC-backed firms in the period following an IPO provides an assessment of the moderating role played by VC investments on the effect of listing on firm growth. Second, and even more important, the above studies do not properly take into account the endogenous nature of VC investments. Firms might attract VC because of observable characteristics (e.g. the human capital of the firm’s founding team) or unobservable characteristics (e.g. their good business prospects). Matching and standard regression techniques can control for selection based on observable factors; the larger the set of these factors, the more likely it is that the estimated treatment effect of VC investments is unbiased. Nonetheless, to the extent that both firm growth and the likelihood of the focal firm being VC-backed are influenced by unobservable factors, lack of proper control for these factors leads to distorted estimates of the effect of VC investments on growth.

To disentangle the treatment and selection effect of VC investments some cross-sectional studies use a two-step approach inspired by the literature on “endogenous treatment” (Heckman, 1990; Vella and Verbeek, 1999). They first consider the likelihood of obtaining VC finance using a selection equation. Then, in analyzing firm growth, they include in the set of covariates an inverse Mill’s ratio type of factor calculated from estimates of the selection equation. Alternatively, VC finance is instrumented through the predicted probability of obtaining such finance. Engel (2002) and Colombo and Grilli (2005, 2010a) use this methodology and document a positive treatment effect of VC investment on the growth of German firms and Italian NTBFs, respectively. Quite interestingly, in these studies there is no evidence of a positive selection effect. In other words, unobservable factors that favor obtaining VC seem

not to be correlated (or even to be negatively correlated) with firm growth.¹

Studies that rely on longitudinal data sets are rare. [Alemany and Martí \(2005\)](#) estimate fixed effects (i.e. within-group, WG) panel data models relating to a sample of Spanish firms that obtained VC. Their results indicate that both the presence of a VC investor in the equity capital of firms and the cumulative amount of VC finance obtained up to a given year result in greater firm size in the same year. [Davila et al. \(2003\)](#) use event analysis to compare the evolution of the number of employees of VC-backed firms in a 7-month time window centered on the month in which VC finance was obtained with that of non-VC-backed firms. They find that VC-backed firms enjoy more rapid growth before and especially after obtaining VC. They also estimate a logit model to investigate whether growth in the first month in which firms are present in the data set influences the likelihood of obtaining VC finance in a subsequent period. Their results suggest that previous firm growth does not attract VC investments.

The panel data methodologies used in these studies again suffer from weaknesses and do not rule out that the positive effect of VC investments detected for firm growth might simply be a consequence of ineffective control of bias arising from selection. On the one hand, WG estimators only control for time-invariant unobserved heterogeneity. On the other hand, VC investments might be attracted by future growth prospects that are unobservable to the econometrician. Hence, even in the absence of any relation between past growth and VC investments, lack of control for unobservable future growth shocks might account for the positive association between VC and firm growth.

3. VC investments in Italian NTBFs

Italy offers an interesting test case to assess whether VC investments have positive effects on the performance of high-tech start-ups. In fact, differently from countries where VC has been mostly studied, such as the US, the UK, and Israel, VC investors in Italy face quite an adverse local environment. Previous studies (see e.g. [Jeng and Wells, 2000](#); [Da Rin et al., 2006](#)) highlight that VC prospers in countries with a well-developed stock market that provides an efficient exit through IPO, a flexible labor market, a large private pension sector, and low capital gains taxation. With the partial exception of capital gains tax Italy performs quite poorly in all these areas. First, historically there were substantial rigidities in the labor market; some of them were removed, but only recently (i.e. since the enforcement of the Biagi law in 2002). Second, private pension funds are almost non-existent. Third, and even more important, the Milan stock exchange is quite small. In Italy the ratio of the market value of listed firms to GDP in 2001 was 48.2% (41.7% in 2004; source, Consob) compared to 138.0% in the US and 151.4% in the UK (source, OECD, Financial Market Trends, October 2004).² Most public firms operate in mature low-tech industries. Accordingly, IPOs are very rare and trade sales are by far the primary exit mechanism for successful VC investments. Between 1997 and 2003 trade sales represented 58% of the number of exits and 63% of the monetary value compared to only 9% and 12% for IPOs according to AIFI. Finally, capital gains tax was very low or even absent in the period under examination. How-

ever, there was no special treatment for early-stage or high-tech investments. This absence relatively favored late-stage investments in mature industries, crowding out early-stage high-tech investments.

Thus, it is not surprising that the Italian VC industry is quite underdeveloped. Early-stage equity financing was almost non-existent up to the mid-1990s. It increased considerably during 1995–2000, reaching a peak of €540 million in 2000, equal to 0.046% of GDP (source: AIFI). Since 2001, early-stage equity financing experienced a dramatic decline and almost vanished in 2004, when there were only 50 investments in 36 companies and the total amount invested was only €23 million (0.002% of GDP). These figures include both high-tech and low-tech investments, but refer exclusively to AIFI members. In particular, as illustrated in Section 4, they do not include most CVC investments made by Italian corporations (for further details on the Italian VC industry see [Bertoni et al., 2006](#)).

There are two reasons why it is interesting to analyze the effect of VC investments on growth in such an hostile environment. First, this situation is common outside common-law countries. According to the VC/PE country attractiveness index developed by [Groh and Liechtenstein \(2009\)](#), Italy scores 47.5, the US scores 100, the UK 84.3, continental Europe 61.3, Asia 54 and eastern Europe 42. Somehow, Italy is more representative of the environment in which VC operates worldwide than the US or the UK. Second, and more important, in countries in which the VC sector is quite underdeveloped and there is a limited number of investors, the effect of selection is likely to differ from the one which has been highlighted in countries with a larger supply of VC. In particular the firms with the best (unobservable) future growth prospects which might materialize also in the absence of VC, might prefer to abstain from looking for VC investments due to the high opportunity cost of this search.

4. Data and sample selection

4.1. The sample

In this paper we use a unique longitudinal data set for a sample of 538 Italian NTBFs observed over a 10-year period (1994–2003). Sample firms were established in 1980 or later, were owner-managed at the time of founding, and remained so up to the end of 2003. Sample firms operate in the following high-tech sectors in manufacturing and services: computers, electronic components, telecommunications equipment, optical, medical and electronic instruments, biotechnology, pharmaceuticals and advanced materials, robotics and process automation equipment, software, Internet, and telecommunications services. Most sample firms are privately held; only 5 firms (1% of the sample) went through an IPO. As several sample firms were established in the second half of the 1990s, we have on average six observations per firm.

The sample is drawn from the 2004 RITA directory and includes all firms that participated in a survey administered in the first semester of 2004. With data on 1974 firms, this directory is the most detailed and comprehensive source of data on Italian NTBFs (see [Appendix A.1](#) for details), and it has been used in several previous studies (see e.g. [Colombo and Grilli, 2005, 2010a](#); [Colombo et al., 2006](#)). It is important to stress that because of the criteria used for inclusion of a firm in the RITA directory, our sample is unlikely to include lifestyle firms and firms that are created purely for tax-saving objectives. Hence, all sample firms can be considered as potential targets of VC investors.

The distribution by industry of operations, geographic area of localization, and foundation date of both the 538 sample firms

¹ [Colombo and Grilli \(2010a\)](#) also estimate an endogenous switching regression model. In addition to an assessment of the treatment effect of VC investments on VC-backed firms, this model also provides an assessment of the growth that non-VC-backed firms would experience if they received VC finance. This latter effect is found to be significantly greater than the former.

² The difference was even greater at the beginning of the 1990s. For instance, [Rajan and Zingales \(2003\)](#) show that in 1990 the ratio of the market value of listed firms to GDP was 13% in Italy compared to 54% in the USA and 84% in the UK.

Table 1

Distribution of sample firms and RITA directory firms by industry, geographic area and foundation date.

	RITA directory		Sample	
	N	%	N	%
Industry				
Internet and telecommunications services	700	35.5	187	34.8
Software	539	27.3	160	29.7
ICT manufacturing ^a	442	22.4	120	22.3
Biotechnology, pharmaceuticals and advanced materials	96	4.9	22	4.1
Automation equipment and robotics	197	9.9	49	9.1
Total	1974	100.0	538	100.0
Geographic area				
Northwest	853	43.2	256	47.6
Northeast	447	22.6	119	22.1
Centre	366	18.6	88	16.4
South	308	15.6	75	13.9
Total	1974	100.0	538	100.0
Foundation date				
1980–1985	345	17.5	79	14.7
1986–1991	350	17.7	98	18.2
1992–1997	622	31.5	224	41.6
1998–2003	657	33.3	137	25.5
Total	1974	100.0	538	100.0

^a ICT manufacturing includes the following sectors: computers, electronic components, telecommunications equipment, optical, medical and electronic instruments.

and the 1974 firms included in the RITA directory is illustrated in Table 1. χ^2 tests reveal no statistically significant differences between the distributions of the sample firms across industries and geographic areas and the corresponding distributions of the population of RITA directory firms from which the sample was drawn ($\chi^2[4]=2.32$ and $\chi^2[3]=4.78$, respectively). Conversely, sample firms are somewhat older than RITA directory firms, with foundation dates more (less) concentrated in the 1992–1997 (1998–2003) period ($\chi^2[3]=29.86$). This bias however does not represent a big issue in this work. In order to assess the effect of VC investments on growth, we need to observe firm performance over time. From this standpoint, very young firms are less interesting than older ones, as the period in which they are observed is shorter.

The use of survey data in addition to data provided by secondary sources (VentureXpert, and data provided by AIFI and by the financial reports of VC investors) allows more accurate coverage of VC investments, especially those made by small and medium size industrial firms, and provides a large information set on sample firms, which is a rarity in this type of study. Hence, we were able to build a rich set of instruments for VC investments and to include controls that might influence both NTB growth and selection by VC investors.

However, a serious problem in our dataset that is common to all survey-based studies (for exceptions see e.g. Delmar and Shane, 2006; Eckhardt et al., 2006) is survivorship bias: only firms that survived up to the survey date could be included in the sample. In principle, attrition might generate a sample selection bias in our estimates. On one hand, NTB failure rates are likely to decrease with access to VC finance because VC-backed firms allegedly benefit from greater endowment of financial and other resources (Puri and Zarutskie, 2008). Moreover, successful VC-backed firms are more likely to be acquired than their non-VC-backed peers as trade sales are an important exit mechanism for VC investors. Hence, the impact of the VC variables on firm growth might actually be greater than that highlighted by our empirical analysis. On the other hand, an opposite bias might also exist, as VC-backed firms might be more risk-prone than non-VC-backed ones and have a lower likelihood of survival (Manigart and Van Hylte, 1999). In fact, we were not able to rigorously control for this selection bias; nonetheless, we implement a partial control that is described in Section 5.2.

4.2. Patterns of VC investments

The distribution by industry, geographic area, foundation date and age on first VC finance round of the VC-backed firms in our sample is illustrated in Table 2. Of the 538 firms in our sample, 58 (10.8%) are VC-backed. This figure clearly overestimates the diffusion of VC among Italian NTBFs because for obvious reasons, VC-backed firms have been oversampled.

χ^2 tests reveal two main differences in the distribution of VC-backed and non-VC-backed sample firms. First, the distribution

Table 2

Distribution of sample VC-backed firms by industry, geographic area, foundation date and age at time of first round of VC finance.

	N	Rate (%)
Industry		
Internet and telecommunications services	30	16.0
Software	10	6.3
ICT manufacturing ^a	12	10.0
Biotechnology, pharmaceuticals and advanced materials	3	13.6
Automation equipment and robotics	3	6.1
Total	58	10.8
Geographic area		
Northwest	27	10.5
Northeast	13	10.9
Centre	14	15.9
South	4	5.3
Total	58	10.8
Foundation date		
1980–1985	8	10.1
1986–1991	9	9.2
1992–1997	16	7.1
1998–2003	25	18.2
Total	58	10.8
Age on first round of VC finance		
0–1	29	50.0
2–5	14	24.1
>5	15	25.9
Total	58	100.0

Rate is the number of VC-backed firms divided by the total number of sample firms in the corresponding category.

^a ICT manufacturing includes the following sectors: computers, electronic components, telecommunications equipment, optical, medical and electronic instruments.

Table 3
Determinants of the likelihood of receiving VC: Cox semi-parametric survival model.

	VC
<i>LSize</i> ($t - 1$)	0.7225 (0.2093)***
<i>DIncubated</i>	-0.5342 (0.5713)
<i>DAlliance at foundation</i>	0.3445 (0.3973)
<i>DASU</i>	0.348 (0.4531)
<i>Stockpatent</i>	0.2448 (0.2118)
<i>DPublic subsidy</i>	-1.1138 (0.5585)**
<i>Ecoeduc</i>	0.426 (0.0939)***
<i>Techeduc</i>	0.0963 (0.0689)
<i>Spec work exp</i>	0.0174 (0.0257)
<i>Other work exp</i>	0.0272 (0.0198)
<i>DManager</i>	0.9941 (0.3104)***
<i>VCarea</i>	0.2399 (0.0853)***
<i>VCsector</i>	0.0727 (0.0278)***
<i>N obs.</i>	3231
<i>N groups</i>	512
Wald χ^2	79.60 [13]***
Proportional hazard test	9.98 [13]

Robust standard deviations in round brackets, degrees of freedom in square brackets. To control for possible misspecification we test the proportional-hazard hypothesis using Schoenfeld (1982) residuals.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

by industry is significantly different ($\chi^2[4]=9.07$), mainly as a result of a higher concentration of VC investments in the Internet and telecommunications services industry. Second, firms established between 1998 and 2003 are significantly more likely to have received VC than those established earlier; this generates a significant difference in the distribution across foundation dates ($\chi^2[3]=10.01$). There is no significant difference between VC-backed and non-VC-backed firms in their distribution across geographic areas ($\chi^2[3]=4.23$).

To provide further insight into the specific characteristics of VC-backed firms and to highlight the determinants of reception of a VC investment, we estimated a semi-parametric Cox (1972) survival type model. The use of Cox proportional hazard models gives maximum flexibility in the specification of the duration dependence of the hazard rate. The results of the estimates are reported in Table 3. The dependent variable of the model is the likelihood of the focal firm obtaining the first round of VC finance after t years from foundation, conditional on not obtaining such finance up to t (i.e. the hazard rate of VC financing). On obtaining VC, the firm enters an absorbing state and no longer contributes to the likelihood function. The set of independent variables includes several firm-specific variables: firm size (*LSize*), measured as the log number of employees (in full-time equivalents and including owner-managers) and lagged by one period; dummies indicating whether the firm was located in a technology incubator (*DIncubated*), benefited at foundation from an alliance with another firm (*DAlliance at foundation*), and is of academic origin (i.e. created by one or more academic founders, *DASU*), and the cumulative number of patents granted to the focal firm up to t (*Stockpatent*). Patents granted are assigned to the year in which the application was made and are discounted through a 0.15 discount factor, as is usual in the literature on innovation economics (see e.g. Griliches, 1992). *DPublic subsidy* is a dummy variable denoting firms that received a public subsidy either from the national government or from local governmental authorities in or before time t . We also consider the human capital of the founding team, measured by founders' years of university-level economic and managerial education (*Ecoeduc*) and technical and scientific education (*Techeduc*), and by years of work experience either in the sector of operation of the focal firm (*Spec work exp*) or in another sector (*Other work exp*). All these variables are averaged across founders. *DManager* is a dummy variable that equals 1 if one or more of the founders previously had a managerial

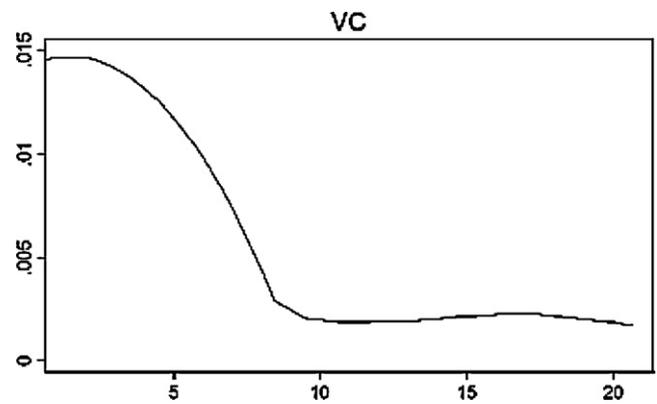


Fig. 1. Baseline hazard rate of receiving the first round of VC finance Legend: The figure shows the baseline hazard rate of obtaining VC. The hazard function is modelled through a semi-parametric Cox proportional-hazard model as $h(t) = h_0(t) \exp(\beta x)$, where $h_0(t)$ is the baseline hazard rate, β a vector of parameters to be estimated, and x the set of covariates. The estimates for β are reported in Table 3.

position in another firm. Finally, *VCarea* and *VCsector* capture the relative density of VC investments in the province (i.e. NUTS3 areas) of localization and industry of operation of the focal firm (source, AIFI).³ We considered here the maximum disaggregation level allowed by AIFI data.

The estimates of the VC model clearly support the argument that VC investments are not random. Therefore, to properly assess their treatment effect on firm growth, controlling for endogeneity is essential. First, the hazard rate is very sensitive to firm age (Fig. 1). It is high in the very early period of firm life; in fact, obtaining VC is significantly more likely at foundation or in the first 2 years of existence than in any subsequent year. After this initial period, the hazard rate decreases quite rapidly with firm age. If firms did not obtain VC in the first 10 years of existence, obtaining VC thereafter is very unlikely. Second, the positive highly significant coefficient of *LSize* indicates that larger firms are more likely to obtain VC finance than their smaller counterparts (see Puri and Zarutskie, 2008 for similar results relating to the US). Third, VC-backed firms are clustered in specific sectors and provinces, as indicated by the significant positive coefficients for *VCsector* and *VCarea*. Fourth, VC investors are attracted by founders with specific human capital characteristics. In particular, with all else equal, firms established by teams of individuals with greater economic and managerial education and prior management experience are more likely to obtain VC finance than other firms. Finally, the likelihood of receiving VC decreases after obtaining a public subsidy, possibly as a consequence of the lower financial needs of firms.

5. Econometric methodology

5.1. Specification of the econometric models

The impact of VC investments on firm growth is investigated through estimation of an augmented Gibrat law dynamic panel-

³ More specifically *VCarea* is calculated as follows. First, we considered the total number of high-tech firms that obtained VC financing over the period 1997–2003 (source: AIFI). Let VCA_k indicate the share accounted for by geographical area k out of this number. Let A_k be the estimated share accounted for by geographical area k (NUTS3 level) out of the total number of Italian NTBFs in 2003 (source: RITA Directory). Then: $VCarea_k = VCA_k / A_k$. As to *VCsector*, it is the ratio of the share accounted for by the sector of the focal NTBF out the total number of high-tech firms that obtained VC financing over the period 1997–2003 (source: AIFI) to the share accounted for by the same sector out of the total number of Italian NTBFs in 2003 (source: RITA Directory).

data model (Chesher, 1979):

$$LSize_{i,t} = \alpha_1 LSize_{i,t-1} + \alpha_2 LAge_{i,t-1} + \beta_1 DVC_{i,t} + W_i + \varepsilon_{i,t}. \quad (1)$$

The starting point is a standard specification in the literature on industrial organization (see e.g. Sutton, 1997; Caves, 1998). $LAge_{i,t-1}$ is the logarithm of the age of firms; $LSize_{i,t-1}$ is the logarithm of the size of firms measured as the number of employees (in full-time equivalents and including owner–managers) or sales. In this framework, the effect of size on firm growth is captured by $(\alpha_1 - 1)$. If the estimated value of α_1 is smaller than unity, firm growth decreases with increasing size. We depart from the standard specification in that we include the dummy variable $DVC_{i,t}$, which indicates the VC status of firms (VC-backed, $DVC_{i,t} = 1$; non-VC-backed, $DVC_{i,t} = 0$). $DVC_{i,t}$ switches from 0 to 1 in the year in which firms obtain their first round of VC finance.⁴ If VC investments positively affect firm growth, we obtain $\beta_1 > 0$.⁵ W_i are unobservable firm-specific time-invariant characteristics and $\varepsilon_{i,t}$ are i.i.d. disturbance terms.

In estimating models (1), we implicitly assume that, after receiving VC, firms indefinitely experience greater growth than in a situation with no VC. In fact, we can presume that the intensity of the treatment effect of VC investment on firm growth might vary over time. For instance, it might be more intense immediately after the first round of VC finance and decrease thereafter. To differentiate the effect of VC on firm growth in the early period after the first round of finance (i.e. in the year in which the first round of VC financing occurs and the subsequent year) from the long-run effect (in the steady state), we estimated another augmented Gibrat law dynamic panel-data model:

$$LSize_{i,t} = \alpha_1 LSize_{i,t-1} + \alpha_2 LAge_{i,t-1} + \beta_1 DVC_{i,t} + \beta_2 DVC2_{i,t} + W_i + \varepsilon_{i,t}. \quad (2)$$

In this specification, $DVC_{i,t}$ switches to unity in the year in which the first round of VC finance occurs, as in model (1), whereas $DVC2_{i,t}$ starts to equal unity in year 2 after the first round of VC finance. Therefore, whereas β_1 reflects the (transitory) effect of VC investment on growth in the early period after the first round of VC, the effect in subsequent years, if any, is captured by $\beta_1 + \beta_2$.

Models (1) and (2) are estimated for an unbalanced panel-data set of 3077 observations for 538 firms (3027 observations for 532 firms in the sales equation) either from 1994 or from their foundation (if after 1994) up to 2003. In Table 4 we report descriptive statistics.

⁴ Note that $VC_{i,t}$ does not switch back to 0 when VC investors exit. The reason is that firms that obtained VC are inherently different from those that never did. For instance, VC finance is assumed to signal the quality of a firm to uninformed third parties, making it easier for the firm to obtain access to additional resources. This effect is likely to persist even after the exit of the VC investor.

⁵ Unfortunately, data on the amount of VC finance received by firms are not available. These data are generally regarded as confidential by owner–managers and could not be obtained from public sources (financial accounts) because the instruments used by VC investors differ (convertible bonds, straight equity, etc.). We also do not know the timing of subsequent rounds of VC finance. Therefore, provided that we find, as we do, that VC investments have a positive treatment effect on firm growth, we cannot quantitatively discern how much of this effect is attributable to the financial resources provided by the VC investors and how much is due to non-financial value added (i.e. to the coaching, monitoring, and signalling functions performed by the VC investor, and to the opportunity for VC-backed NTBFs to take advantage of the investor's network of social contacts). We acknowledge this as a limitation of the present study. However note that on this issue we collected qualitative evidence through interviews with owner–managers that will be illustrated in Section 7.2.

Table 4
Descriptive statistics.

Variable	Obs.	Mean	S.D.	Min	Max
<i>Ln(Employees)</i>	3686	2.084	1.119	0.000	6.452
<i>Ln(Sales)</i>	3628	12.984	1.767	6.748	18.919
<i>Ln(Age)</i>	3686	1.819	0.860	0.000	3.1780
<i>DIncubated</i>	3671	0.071	0.256	0.000	1.000
<i>DAlliance at foundation</i>	3686	0.069	0.253	0.000	1.000
<i>DASU</i>	3686	0.098	0.297	0.000	1.000
<i>Stockpatent</i>	3686	0.087	0.585	0.000	19.317
<i>DPublic subsidy</i>	3686	0.204	0.403	0.000	1.000
<i>Ecoeduc</i>	3622	0.274	0.827	0.000	5.000
<i>Techeduc</i>	3622	1.819	2.203	0.000	8.000
<i>Spec work exp</i>	3584	4.058	6.126	0.000	35.500
<i>Other work exp</i>	3534	7.455	8.006	0.000	49.000
<i>DManager</i>	3653	0.249	0.433	0.000	1.000
<i>VCarea</i>	3686	1.078	1.199	0.000	5.892
<i>VCsector</i>	3686	1.777	2.952	0.000	28.314

5.2. Estimation methodology

The inclusion in all models of the lagged dependent variable as one of the covariates and the endogenous nature of the relationship between VC investment and firm size require the use of appropriate estimation techniques. This latter aspect is crucial for the purpose of the present study. A positive association between VC investment and firm growth may simply be the result of a selection effect: VC investors might simply pick NTBFs with good future growth prospects without providing them with any support of either a financial or non-financial nature. This problem is likely to be especially serious for NTBFs, because their growth performance is closely related to unobservable characteristics such as innovative business ideas, development of a unique technology, or a team of smart owner–managers. If these unobservable factors also influence the ability of firms to attract VC investors, a spurious correlation between VC investment and growth follows because of unobserved heterogeneity. An opposite bias is also possible if NTBFs with superior growth prospects self-select out of the VC market. In a thin VC market, finding a suitable offer from a VC investor might be difficult; with owner–manager time being the scarcest NTBF resource, the opportunity costs of search for a VC investor are clearly higher the better the prospects of the firm. As long as VC regressors are correlated with the error terms $\varepsilon_{i,t}$, their coefficients in a simple pooled ordinary least squares (OLS) regression are biased. The same argument applies to the coefficients in WG estimates if the unobservable shocks are time-varying.

To address these endogeneity problems, following the literature on dynamic panel-data models (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998) we use GMM estimates. For comparison, we also report pooled OLS and WG estimates. In applying GMM techniques to the estimates of models (1) and (2), we follow a build-up approach similar to that proposed by Bond (2002). As argued by Winship and Morgan (1999), there is no “econometric panacea” for endogeneity, in that there is no single econometric method that can solve the problem. Consequently, several GMM estimators are used. Relying on different (in most cases testable) assumptions for the instruments for the VC variables presents different pros and cons. However, when different estimation methods lead to similar results, this clearly supports the robustness of the findings (see the Appendix A.2 for a more technical comparison of the orthogonality conditions of different GMM estimators).

We initially use a GMM-DIF estimator (first-differenced) (Arellano and Bond, 1991). The growth equations are first-differenced to eliminate any possible correlation between the regressors and the individual fixed effects W_i . This procedure controls for time-invariant unobserved heterogeneity. Then the model

is estimated in first differences using an appropriate lag structure for the variables in levels as instruments for the differenced regressors to deal with potential endogeneity caused by time-varying unobserved heterogeneity. In doing this we make the conservative assumption that the VC variables and *LSize* are endogenous; therefore, instruments start from $t-2$.

As shown by Blundell and Bond (1998), the GMM-DIF estimator is subject to serious finite-sample bias when series are highly persistent⁶ (i.e. have near unit-root properties), and consequently instruments in levels for first-difference equations are weak. The problem is usually tackled by increasing the set of moment conditions used in the estimation. For this purpose, we use a GMM-SYS (system) estimator. In particular, other than using lagged levels of the series as instruments for first-difference equations, additional moment conditions are used with first differences as instruments for equations in levels, starting from $t-1$ for $\Delta LSize$ and for the ΔVC variables.

This GMM-SYS estimator also has some weaknesses. First, the use of a large number of instruments can result in significant finite-sample bias. Moreover, measurement errors can cause potential distortions. To deal with these problems (Bond, 2002) we re-estimate the model with a reduced instrument set using moment conditions in the interval between $t-3$ ($t-2$) and $t-6$ ($t-5$) for instruments in levels (differences). Postponing VC instruments to the third lag is also useful for ensuring that the estimates are robust to measurement errors regarding the exact timing of VC investment, or, rather, its effect on firm growth.

Second, the moment conditions of the GMM-SYS approach are only valid if the additional instruments are uncorrelated with the error terms or, in other words, if deviations of dependent and independent endogenous variables from the long-run mean are uncorrelated with any unobservable or observable individual fixed effect. The appropriateness of this stationary mean assumption is questionable on *a priori* grounds because it requires, for example, that size shocks do not depend on unobserved firm-specific effects. However, results for the Hansen statistic confirm the validity of the moment conditions used in all estimations. Moreover, pseudo-first-stage regressions (provided in Appendix A.3) confirm the suitability of the GMM-SYS estimator with respect to the GMM-DIF estimator. They highlight that lagged instruments in first differences are strongly correlated with the VC variables, pointing to the strength other than the validity of the additional instruments, whereas lagged instruments in levels are poorly correlated with the change in VC backing status. This notwithstanding, the GMM-SYS estimator relies on specific assumptions as to the validity of the differenced instruments for which we can only partially control through the results of the (difference) Hansen tests (Bond, 2002, p. 156). To relax these assumptions, we use an estimator originally proposed by Ahn and Schmidt (1995) that adds a set of non-linear moment conditions to the GMM-DIF estimator. These follow from the standard assumptions in dynamic panel-data models and require the milder assumption that the individual effects W_i and the disturbances ε_{it} are uncorrelated (Bond, 2002; Baltagi, 2003).⁷

Third, the standard GMM approach enables us to control for the endogeneity of VC investments under the assumption of sequential exogeneity (see e.g. Wooldridge, 2002, p. 300). In fact, it assumes that *future* shocks to firm size are independent of VC investments whereas *past* shocks can affect them. It might be argued that because of superior scouting capabilities, VC investors can identify firms with future high growth prospects that are unobservable to other investors. Under these circumstances, we would expect VC investments to be positively correlated to future size shocks.⁸ As a corollary, the estimated coefficients of the VC variables in a standard GMM framework would be upwardly biased. In other words, we would mistakenly attribute a positive effect of VC investments on firm growth to the influence of VC investors on portfolio firms, which instead arises because of selection of better firms.

To address these problems we use three different estimation strategies. First, we add two variables to the set of instruments of the GMM-SYS estimator that reflect the presence and activism of VC investors in the geographic area in which the focal NTBF is located ($VCArea_i$) and in the industry in which it operates ($VCSector_i$). The logic is similar to that followed by Sørensen (2007) in that it exploits the abundance or scarcity of VC in markets relevant to the focal firm (either the geographic or industry market) to control for the effect of selection. However, our economic problem is different from that of Sørensen (2007) and so is the econometric implementation of this logic. Good instruments need to be related to the VC variables but independent of the error terms of the growth equation, which reflect the unobserved growth prospects of the firm. Firms with the best growth prospects might be located in geographic areas or operate in industries with an abundance or scarcity of VC. Given firm's growth prospects, the likelihood of obtaining VC finance is higher if a greater number of active VC investors are available. However, the effect of VC investment on growth is independent of these market-level characteristics and thus they are a source of exogenous variation (in a similar vein see Bottazzi et al., 2008; Chemmanour et al., 2008; Ivanov and Xie, 2010).⁹

Second, as illustrated in Section 4.2, we estimate a selection equation for the hazard rate of NTBFs obtaining VC t years after foundation using a semi-parametric survival model. We use these estimates to compute the probabilities of the focal NTBF receiving VC in t and insert these values as additional instruments in the GMM-SYS estimation of Eq. (1) (for a very similar procedure, albeit in a different context, see Benfratello and Sembenelli, 2006).

Third, we adapt a typical Heckman (1978, 1979) two-step sample selection approach to our longitudinal setting. Estimates of the VC selection equation are used to compute a correction term based on the Lee (1983) generalization of the Heckman (1979) two-stage selection model (see Eckhardt et al., 2006 for an identical methodology for selection correction). This inverse Mill's ratio type of control factor is included in a WG regression of the subset of firms that received VC finance in the observation period (firms that did not receive VC finance were excluded from these second-stage esti-

⁸ We assume here that NTBFs with future high growth prospects attract VC investments and that these firms would be able to realise their growth potential even in the absence of VC (see Sørensen, 2007 for a thorough discussion of the role and influence of sorting in assessing the effect of the experience of VC investors on the likelihood of portfolio companies going through an IPO). Conversely, owing to information asymmetries in capital markets, NTBFs might be financially constrained in spite of their (unobservable) future growth prospects and might not be able to find the finance needed to exploit these growth opportunities from sources other than VC investors. In this situation, as financial constraints are relaxed because of receipt of VC, VC investors are responsible for the firm growth realised (Bertoni et al., 2010a).

⁹ Note that, in accordance with the studies mentioned above, we assume that clustering of VC investments in a specific industry or geographic market is exogenous and is not driven by the inherent growth prospects unobserved by third parties of NTBFs in those markets that are potential candidates for VC investment.

⁶ On this issue, see Bond (2002). Although unit roots for employees and sales are excluded by the test proposed by Levin et al. (2002) (t -test: 37.96 and 48.85, respectively), persistence is nonetheless present (e.g. OLS estimates of the autoregressive parameters are 0.9402 and 0.9032 for employment and sales, respectively).

⁷ The methodology of Ahn and Schmidt (1995), albeit technically elegant, is computationally rather complex and full convergence in the estimation algorithm may not be reached, even after many iterations. Moreover, its empirical implementation is not immediately applicable using standard econometric software-packages. We are indebted to Seung Ahn, who provided useful suggestions on how to implement the augmented GMM estimator she proposed.

mates) to control for the unobserved heterogeneity that affects both the selection equation and the growth equation.¹⁰

Finally, we test for a possible survivorship bias. For this purpose, we adapt to our specific framework the standard Wooldridge (1995) variable addition test for selection bias in panel data (see also Baltagi, 2003, p. 223) and more precisely a more recent methodology proposed by Semykina and Wooldridge (2010) that extends the previous one by allowing the test in the presence of unobserved heterogeneity and endogenous regressors.¹¹ We initially focused attention on the RITA 2000 sample. This sample, composed of 401 firms, was selected according to the same criteria and strategy used for the sample examined in the present study (Colombo et al., 2004). Some 31 sample firms were VC-backed at the beginning of 2000. We examined the exit rate of sample firms in the period 2000–2003. Twelve VC-backed firms either ceased operations or were acquired (38.7%). Some 89 non-VC-backed firms exited the sample in this period (24.1%). Then we estimated a probit model of firm exit in 2000–2003 conditional on survival up to the end of 1999; the dependent variable in this model is the hazard rate of exit of sample firms in 2000–2003. The independent variables include human capital variables, receipt of VC investment before 2000, firm-specific characteristics (i.e. firm size and age in 1999), and other controls. We used the estimated coefficients for this sample selection model to compute the inverse Mill's ratio of exit for each firm-year observation included in the sample analyzed in the present work.¹² This time-varying ratio was then inserted as a control for survivorship bias in growth Eq. (1) which is then estimated via an instrumental variable approach, such as the GMM-SYS, as indicated by Semykina and Wooldridge (2010).¹³

To evaluate the relevance of all our econometric models, we apply different diagnostic tests that are standard in the GMM-context. First, we implement the Arellano and Bond test for first- and second-order serial autocorrelation of residuals [AR(1), AR(2)]. If ε_{it} is not serially correlated, the difference of residuals should be characterized by a negative first-order serial correlation and the absence of a second-order serial correlation. The Hansen test for the validity of over-identifying restrictions is implemented for each regression. This statistic tests the null hypothesis that the specified orthogonality conditions are equal to zero (Hansen, 1982).

6. Econometric results

6.1. Effect of VC investment on firm growth

Table 5 shows the results of the estimation of Eq. (1) using the different GMM estimators described in the previous section (columns GMM-DIF to GMM-SYS (4)), with firm size measured as the number of employees (Panel A) and sales (Panel B). In all models the null hypothesis of the absence of a negative first-order serial correlation between differenced residuals is rejected, whereas the null hypothesis of the absence of a second-order serial correlation is not

(with one exception in the estimates of the sales equation). Hansen tests also indicate that the null hypothesis of equality to zero of the specified orthogonality conditions is not rejected (again with one exception). Column HSS reports estimates of the WG Heckman-type sample selection model. We also report pooled OLS and simple WG estimates for comparison purposes.

Independently of the specific econometric technique, the estimates of model (1) consistently reveal that VC investments have a positive treatment effect on the growth rate of NTBFs. The coefficients for $DVC_{i,t}$ are positive and significant at conventional confidence levels in all estimates of the employment equation. The same is true for the sales equation, with only one exception relating to the GMM-DIF estimates; however, as noted earlier, the instruments in levels are rather weak in these estimates. The coefficient for the inverse Mill's ratio control for sorting [IMR(VC)] in the WG estimates reported in column HSS is not significant in the employment equation and is negative and weakly significant in the sales equation. In other words, unobserved factors that are positively associated with firm growth seem to be either negatively correlated (sales growth) or not correlated (employment growth) with selection of firms by VC investors. In contrast to results for US firms in previous studies (e.g. Sørensen, 2007; Chemmanour et al., 2008), there is no evidence in our data that VC investors pick companies with the best unobserved future growth prospects.

It is interesting to assess the magnitude of the positive treatment effect of VC investment on firm growth. The estimated coefficient for $DVC_{i,t}$ is a measure of the average growth rate of a VC-backed firm in the year of the first VC round above the rate the same firm would experience in the absence of VC. The value of this coefficient can also be interpreted as the percentage difference between the size of a VC-backed firm at the end of this year and that of a non-VC-backed but otherwise identical firm. Our estimates suggest that the influence of VC investment on firm growth is economically significant. The additional growth rate attributable to VC financing is approximately 40% for both the number of employees and sales. However, there is considerable variation across estimators in the estimated magnitude of this effect. In the employment equation its magnitude ranges from 22% to 142%. In the sales equation the range is even greater. It is also interesting to gauge the longer-term impact of VC on firm growth. Owing to the recursive nature of the model specification, this exercise is not trivial. More precisely, we want to compare the estimated size of a VC-backed firm T years after the first VC round with the size the firm would exhibit in the absence of VC. This difference (in percentage) is equal to $\hat{E}_{VC(T)}$:

$$\hat{E}_{VC(T)} = \beta_1 \sum_{\tau=0}^T \alpha_1^\tau. \tag{3}$$

Since $\alpha_1 < 1$ (see *infra*), we can also estimate the theoretical long-run effect of VC on firm size using the following expression:

$$\hat{E}_{VC(\infty)} = \lim_{T \rightarrow \infty} \hat{E}_{VC(T)} = \frac{\beta_1}{1 - \alpha_1}. \tag{4}$$

We can test the null hypothesis that the firm size increase caused by VC investment is null using a χ^2 test performed by the Delta method (for a similar approach in a different context see Maliranta, 2005; Bertoni et al., 2010a). Quite interestingly, when we consider longer time horizons the difference in the estimated effect of VC investment across different estimation techniques decreases. For instance, the employment increase attributable to VC 4 years after the first VC round (i.e. $\hat{E}_{VC(4)}$) estimated using different GMM models and HSS varies between +97% and +218%; these values are similar to those estimated by Puri and Zarutskie (2008) for US firms. In summary, even though it is difficult to be precise about the magnitude of the treatment effect of VC investment on firm growth, our estimates unanimously indicate that this effect is positive and

¹⁰ The functional form of this added regressor is $\lambda_{it} = \phi[\Phi^{-1}(F_i(t))] \cdot (1 - F_i(t))^{-1}$, where $F_i(t)$ is the cumulative hazard function for VC backing of firm i at time t , ϕ is the standard normal density function and Φ^{-1} is the inverse of the standard normal distribution function.

¹¹ We have followed as closely as possible the two above-mentioned test approaches given our data constraints. In particular, since we estimate a single probit equation for firm exit, the only major simplification with respect to Wooldridge's original framework and its subsequent extension is the assumption that the impact of each determinant of firm exit does not vary over time.

¹² Formally: $\lambda_{it}^{EXIT} = -\phi(\psi/w_{it}) \cdot \Phi(\psi/w_{it})^{-1}$, where w_i is the vector of independent variables of the probit model on firm exit, and $\phi(\cdot)$ and $\Phi(\cdot)$ are the density and distribution functions, respectively, of the standard normal.

¹³ The inverse Mill's ratio in the Semykina and Wooldridge (2010) test is treated as an exogenous covariate (we thank Anastasia Semykina for personal communication confirming this as the correct procedure).

Table 5
Effect of VC investments on firm growth.

	GMM-DIF	GMM-SYS (1)	GMM-SYS (2)	AHN-SCHMIDT	GMM-SYS (3)	GMM-SYS (4)	HSS	OLS	WG
Panel A: Employees									
<i>LSize</i> (<i>t</i> – 1)	0.2777 (0.0929) ^{***}	0.8420 (0.0460) ^{***}	0.9273 (0.0414) [*]	0.4314 (0.0454) ^{***}	0.8522 (0.0446) ^{***}	0.9026 (0.0302) ^{***}	0.6637 (0.0885) ^{***}	0.9402 (0.009) ^{***}	0.5239 (0.025) ^{***}
<i>LAge</i> (<i>t</i> – 1)	0.3194 (0.0900) ^{***}	–0.0202 (0.0427)	–0.0784 (0.0513)	0.2715 (0.05) ^{***}	–0.0343 (0.0387)	0.0183 (0.0409)	–0.0725 (0.1114)	–0.0245 (0.012) ^{**}	0.2422 (0.028) ^{***}
<i>DVC</i> (<i>t</i>)	1.4194 (0.5762) ^{**}	0.4270 (0.0968) ^{***}	0.2236 (0.0949) ^{**}	1.2559 (0.3657) ^{***}	0.4102 (0.095) ^{***}	0.3934 (0.0739) ^{***}	0.3878 (0.0894) ^{***}	0.2309 (0.032) ^{***}	0.2791 (0.065) ^{***}
<i>IMR</i> (<i>VC</i>)							0.0181 (0.1662)		
Sector dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	No
<i>N</i>	2526	3077	3077	2526	3077	2664	259	3077	2526
<i>N</i> groups	509	538	538	509	538	508	53		509
AR(1)	–3.37 ^{***}	–8.68 ^{***}	–8.74 ^{***}		–8.74 ^{***}	–9.10 ^{***}			
AR(2)	–1.42	–0.46	–0.49		–0.46	–0.32			
Hansen test	67.51 [85]	115.06 [102]	67.22 [62]		117.03 [104]	109.82 [101]			
$\hat{E}_{VC(T)}$									
<i>T</i> = 1	1.8135 ^{**} (0.020)	0.7865 ^{***} (0.1618)	0.4310 ^{**} (0.1746)	1.7978 ^{***} (0.5117)	0.7597 ^{***} (0.1607)	0.7486 (0.1330) ^{***}	0.6451 (0.1422) ^{***}	0.4481 ^{***} (0.6126)	0.4254 ^{***} (0.9746)
<i>T</i> = 2	1.9229 ^{**} (0.8530)	1.0892 ^{**} (0.2035)	0.6233 ^{**} (0.2410)	2.0316 ^{***} (0.5734)	1.0577 ^{***} (0.2046)	1.0691 ^{***} (0.1804)	0.8160 (0.1807) ^{***}	0.6522 ^{**} (0.0883)	0.5020 ^{***} (0.1146)
<i>T</i> = 3	1.9533 ^{**} (0.8793)	1.3441 ^{***} (0.2288)	0.8016 ^{***} (0.2957)	2.1324 ^{***} (0.6004)	1.3112 ^{***} (0.2327)	1.3584 ^{***} (0.2187)	0.9293 (0.2128) ^{***}	0.8441 ^{***} (0.1133)	0.5421 ^{***} (0.1236)
<i>T</i> = 4	1.9617 ^{**} (0.881)	1.5587 ^{***} (0.2429)	0.9669 ^{***} (0.3402)	2.1759 ^{***} (0.6123)	1.5279 ^{***} (0.2499)	1.6196 ^{***} (0.2537)	1.0046 (0.2403) ^{***}	1.0246 ^{**} (0.1365)	0.5631 ^{***} (0.1284)
<i>T</i> → ∞	1.9650 ^{**} (0.8923)	2.703 ^{***} (0.4057)	3.0744 ^{***} (0.8093)	2.2090 ^{***} (0.6216)	2.7760 ^{***} (0.4493)	4.0402 (0.9386) ^{***}	1.1532 ^{***} (0.3372)	3.8625 ^{***} (0.6176)	0.5863 ^{***} (0.1339)
Panel B: Sales									
<i>LSize</i> (<i>t</i> – 1)	0.2720 (0.1097) ^{***}	0.7660 (0.0620) ^{***}	0.9240 (0.0476)	0.1307 (0.0435) ^{***}	0.7649 (0.0616) ^{***}	0.9237 (0.0399) [*]	0.3205 (0.1489) ^{**}	0.9032 (0.0114) ^{***}	0.4199 (0.0279) ^{***}
<i>LAge</i> (<i>t</i> – 1)	0.5559 (0.177) ^{***}	–0.1374 (0.0808) [†]	–0.2205 (0.0747) ^{***}	0.7051 (0.1086) ^{***}	–0.1324 (0.0796) [†]	–0.2774 (0.7643) ^{***}	0.5214 (0.2993) [†]	–0.1537 (0.021) ^{***}	0.3221 (0.0485) ^{***}
<i>DVC</i> (<i>t</i>)	0.9486 (1.0887)	0.4267 (0.1328) ^{***}	0.1625 (0.0951) [†]	2.2250 (0.6672) ^{***}	0.4327 (0.1318) ^{***}	0.2308 (0.1008) ^{**}	0.4542 (0.1490) ^{***}	0.2640 (0.0559) ^{***}	0.4939 (0.1141) ^{***}
<i>IMR</i> (<i>VC</i>)							–0.3713 (0.2069) [†]		
Sector dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	No
<i>N</i>	2481	3027	3027	2481	3027	2620	251	3027	2481
<i>N</i> groups	504	532	532	504	532	502	52		504
AR(1)	–2.64 ^{***}	–6.22 ^{***}	–6.25 ^{***}		–6.22 ^{***}		–6.12 ^{***}		
AR(2)	1.53	1.52	1.54		1.52	1.90 [†]			
Hansen test	99.20 [84]	113.89 [101]	68.82 [62]		115.20 [103]	120.81 [100] [†]			
$\hat{E}_{VC(T)}$									
<i>T</i> = 1	1.2067 (1.3979)	0.7536 (0.2148) ^{***}	0.3126 (0.1776) [†]	2.5159 (0.8276) ^{***}	0.7638 (0.2128) ^{***}	0.4252 (0.1868) ^{**}	0.5997 (0.2165) ^{***}	0.5024 (0.1051) ^{***}	0.7013 (0.1627) ^{***}
<i>T</i> = 2	1.2769 (1.4883)	1.0039 (0.2643) ^{***}	0.4514 (0.2490) [†]	2.5540 (0.8589) ^{***}	1.0170 (0.2613) ^{***}	0.6444 (0.2600) ^{**}	0.6464 (0.2522) ^{**}	0.7177 (0.1483) ^{***}	0.7884 (0.1842) ^{***}
<i>T</i> = 3	1.2960 (1.5147)	1.1957 (0.2936) ^{***}	0.5796 (0.3108) [†]	2.5589 (0.8643) ^{***}	1.2107 (0.2899) ^{***}	0.8293 (0.3216) ^{***}	0.6613 (0.2686) ^{**}	0.9123 (0.1865) ^{***}	0.8249 (0.1937) ^{***}
<i>T</i> = 4	1.3012 (1.5224)	1.3427 (0.3110) ^{***}	0.6980 (0.3643) [†]	2.5596 (0.8651) ^{***}	1.3588 (0.3067) ^{***}	1.0010 (0.3736) ^{***}	0.6613 (0.2754) ^{**}	1.0880 (0.2203) ^{***}	0.8403 (0.1980) ^{***}
<i>T</i> → ∞	1.3031 (1.5255)	1.8237 (0.3638) ^{***}	2.1390 (0.9835) ^{**}	2.5597 (0.8653) ^{***}	1.8410 (0.3596) ^{***}	3.2400 (1.0156) ^{***}	0.6683 (0.2796) ^{**}	2.7280 (0.5182) ^{***}	0.8514 (0.2014) ^{***}

The estimates refer to Eq. (1). Columns *GMM-DIF* and *GMM-SYS* (1) report, respectively, difference and system GMM estimates. Column *GMM-SYS* (2) reports system GMM estimates based on a reduced set of instruments with moment conditions in the interval between *t* – 3 and *t* – 6 for equations in differences and between *t* – 2 and *t* – 5 for the equations in levels. Column *AHN-SCHMIDT* reports GMM estimates based on linear and non-linear moment conditions as shown by Ahn and Schmidt (1995). Column *GMM-SYS* (3) reports system GMM estimates with the addition, among instruments, of *VCArea* and *VCSector*, which capture respectively the relative density of VC investments in the province (i.e. NUTS3 areas) of localization and industry of operation of the firm. Column *GMM-SYS* (4) reports system GMM estimates with the addition, among instruments, of the estimated probability of a firm being VC-backed based on the Cox proportional-hazard model estimates reported in Table 3. Column *HSS* reports WG (fixed-effects) regression on the subsample of VC-backed firms with the addition of an Inverse Mill's ratio control for non-exogeneity in VC selection based on the Cox proportional-hazard model estimates reported in Table 3. AR(1) and AR(2) are tests of the null hypothesis of respectively no first- or second-order serial correlation. Hansen is a test of the validity of the overidentifying restrictions based on the efficient two-step GMM estimator. All GMM estimates are based on the hypothesis of VC being endogenous, which implies its use as instrument in GMM models, dated at least *t* – 2 (*t* – 3 in *GMM-SYS*(3)) for the equations in first differences and at least *t* – 1 for the equations in levels (*t* – 2 for *GMM-SYS*(3)). $\hat{E}_{VC(T)}$ is the estimated effect of VC *T* years after the first VC round; it is given by Eqs. (3) and (4) and is computed by the Delta method. All GMM estimates are based on a two-step model with robust standard errors and finite sample correction (Windmeijer, 2005). *HSS*, *OLS* and *WG* models are computed with robust standard errors (White, 1980). Standard deviations in round brackets, degrees of freedom in square brackets. The *p*-value relating to the coefficient of *LSize*(*t* – 1) refers to the null hypothesis that its coefficient equals unity.

^{*} *p* < .10.

^{**} *p* < .05.

^{***} *p* < .01.

Table 6
Evolution over time of the impact of VC investment on firm growth.

	Employees	Sales
Panel A: Results of the estimates		
<i>LSize</i> (<i>t</i> – 1)	0.8597 (0.0495)***	0.7714 (0.0675)***
<i>LAge</i> (<i>t</i> – 1)	–0.0329 (0.0465)	–0.1361 (0.0862)
<i>DVC</i> (<i>t</i>)	0.5921 (0.0952)***	0.4929 (0.1631)***
<i>DVC2</i> (<i>t</i>)	–0.2431 (0.0571)***	–0.1121 (0.1655)
Sector dummies	Yes	Yes
<i>N</i>	3077	3027
<i>N</i> groups	538	532
AR(1)	–8.9***	–9.38***
AR(2)	–0.75	–0.82
Hansen test	100 [101]	94.92 [122]
Panel B: $\hat{E}_{VC(T)}$		
<i>T</i> = 0	0.5921 (0.0952)***	0.4929 (0.1631)***
<i>T</i> = 1	1.1011 (0.1556)***	0.8731 (0.2718)***
<i>T</i> = 2	1.2956 (0.1714)***	1.0543 (0.2911)***
<i>T</i> = 3	1.4629 (0.1851)***	1.1942 (0.3321)***
<i>T</i> = 4	1.6066 (0.1934)***	1.3020 (0.3722)***
<i>T</i> → ∞	2.4873 (.4057)***	1.6660 (0.5214)***

All estimates are based on a two-step system GMM model with robust standard errors and finite sample correction (Windmeijer, 2005). AR(1) and AR(2) are tests of the null hypothesis of respectively no first- or second-order serial correlation. Hansen is a test of the validity of the overidentifying restrictions based on the efficient two-step GMM estimator. Estimates are based on the hypothesis of *DVC* being endogenous, which implies their use as instruments in GMM models dated at least *t* – 2 for the equations in first differences and at least *t* – 1 for the equations in levels. The *p*-value relating to the coefficient of *LSize*(*t* – 1) refers to the null hypothesis that its coefficient equals unity. Panel B reports the estimated effect of VC, as described in Eq. (5), based on estimates reported in Panel A by using the Delta method. Standard deviations in round brackets, degrees of freedom in square brackets.

* *p* < .10.
** *p* < .05.
*** *p* < .01.

of sizeable magnitude, independent of whether size is measured as employment or sales. Moreover, different estimation methods seem to differ more in the timing of the effect of VC rather than in its long-term magnitude.

As a final remark, we briefly consider the estimated effects of firm size on growth rates. The coefficient for firm size is significantly smaller than unity in both the employment and sales equations. This is consistent with the stylized fact highlighted by the empirical literature on the Gibrat law (e.g. Sutton, 1997; Caves, 1998) that smaller firms tend to grow faster than larger firms. The magnitude of this coefficient is smaller, and so the negative effect of size on growth is larger in the GMM-DIF, Ahn & Schmidt and WG estimates, i.e. when cross-sectional variations among firms are not used in the estimates (for similar results see Goddard et al., 2002). The estimated coefficient for firm age is negative in all the estimates that use cross-sectional variations across firms, but is never significant. Conversely, it is positive and significant when these cross-sectional variations are not used (for analogous results see e.g. Huynh and Petrunia, 2006).

6.2. Dynamics of the effect of VC investment on firm growth

To analyze in more detail the dynamics of the treatment effect of VC investments on firm growth we estimate Eq. (2). Results are reported in Table 6.¹⁴

Again, owing to the recursive nature of the models, the estimated effect of VC *T* years after the first round of VC investment is given by a non-linear combination of the estimated parameters. In

this case it takes the following form:

$$\hat{E}_{VC(T)} = \beta_1 \sum_{\tau=0}^T \alpha_1^\tau \quad \text{if } T < 2$$

$$\hat{E}_{VC(T)} = \beta_1 \sum_{\tau=0}^T \alpha_1^\tau + \beta_2 \sum_{\tau=0}^{T-2} \alpha_1^\tau \quad \text{if } T \geq 2$$

$$\hat{E}_{VC(\infty)} = \lim_{t \rightarrow \infty} \hat{E}_{VC(T)} = \frac{\beta_1 + \beta_2}{1 - \alpha_1}$$
(5)

Hence, parameter β_1 determines the effect of VC in the year in which VC finance is first obtained and in the following year (i.e. the short-run effect). The effect from year 2 onwards depends on the sum of parameters β_1 and β_2 .¹⁵

The estimates of Eq. (2) for employees and sales reported in Panel A show that VC has a much stronger effect in the short run than in the long run, since β_1 is positive and β_2 is negative in both models (albeit β_2 is significant only for employees). As shown in Panel B, whereas the long-term treatment effect of VC investment is positive (i.e. $\beta_1 + \beta_2 > 0$) and its magnitude is similar to that estimated using model (1), most of this positive treatment effect is obtained immediately after receipt of the first VC round (for similar results for US firms see again Puri and Zarutskie, 2008). In terms of the number of employees, the size of a VC-backed firm at the end of the year after that of the first VC round is 110% greater than in the absence of VC. If growth continued until the firm reached a steady state, it would be 249% larger than in the absence of VC. A similar pattern is obtained in the sales model. More than half of the treatment effect of VC investment on sales growth is obtained in the year immediately after that of the first VC round (+87% versus +167%).

6.3. Additional evidence on the effects of VC investment on firm growth

In the previous sections we documented that VC investments have a positive treatment effect on the employment and sales growth of firms. We are confident that these results are not driven by unobserved heterogeneity, with VC investors simply investing in firms with superior future growth prospects. In this section, we first present some robustness checks that confirm the evidence. In particular, we insert in growth Eq. (1) time-varying controls capturing firm-specific characteristics that might influence both the likelihood of obtaining VC and firm growth. More precisely, we consider: (i) the (discounted) stock of patents granted to a firm up to *t* (*Stockpatent*_{*i,t*}); and ii) a dummy variable indicating receipt of a public subsidy in or before *t* (*DPublicSubsidy*_{*i,t*}). Innovative NTBFs may draw on their patented technologies to grow larger than their less innovative counterparts. Moreover, to the extent that NTBFs are financially constrained, receipt of a public subsidy, while relaxing these constraints, might favor growth. The estimates of GMM-SYS models equivalent to those in column 3 (GMM-SYS(1)) in Table 5 are reported in Table 7 as for employment and sales growth. The coefficient for *Stockpatent* is never significant. The coefficient for *DPublicSubsidy* is not significant in the employment equation, but is positive and (weakly) significant in the sales equation. More interestingly, the estimates confirm the positive treatment effect of VC investment.

¹⁵ The distinction between short- and long-run effects is somewhat arbitrary. We also tested alternative definitions (results are omitted here for brevity). When the threshold is postponed, results converge to the “static” version of Eq. (1). When it is anticipated as the year following the first VC round, greater measurement errors are obtained because the exact time in which VC finance was received during year 0 is unknown.

¹⁴ For simplicity, we only report GMM-SYS estimates (GMM-SYS 1). Results of the estimates obtained using other estimators are reasonably close to those presented here and are available from the authors on request.

Table 7
Robustness checks.

	Employees		Sales	
	Controls	Survivorship	Controls	Survivorship
$LSize(t-1)$	0.8480 (0.0459)	0.8806 (0.053)**	0.8055 (0.057)***	0.7144 (0.0936)***
$LAge(t-1)$	-0.0338 (0.0366)	-0.0463 (0.0636)	-0.1236 (0.0734)*	-0.0092 (0.1622)
$DVC(t)$	0.4194 (0.0993)***	0.4464 (0.1357)***	0.4067 (0.1259)***	0.3223 (0.1391)**
$Stockpatent$	-0.9431 (0.7273)		-0.3815 (1.3732)	
$DPublic\ subsidy$	-0.3242 (0.8280)		2.8033 (1.4475)*	
$IMR(Survived)$		-0.5531 (0.6200)		0.6332 (0.8507)
Sector dummies	Yes	Yes	Yes	Yes
N	3077	2950	3027	2900
N groups	538	517	532	511
AR(1)	-8.70***	-8.34***	-6.37***	-5.61***
AR(2)	-0.38	-0.50	1.30	1.63
Hansen test	131.98 [159]	104.54 [99]	126.15 [158]	104.67 [98]
$\hat{E}_{VC(\infty)}$	2.7603 (0.4420)***	3.7390 (1.5083)**	2.0907 (0.3887)***	1.1285 (0.5649)**

All estimates are based on a two-step system GMM model with robust standard errors and finite sample correction (Windmeijer, 2005) under the hypothesis of DVC being endogenous, which implies their use as instruments since $t-2$ for the equations in first differences and $t-1$ for the equations in levels. AR(1) and AR(2) are tests of the null hypothesis of respectively no first- or second-order serial correlation. Hansen is a test of the validity of the overidentifying restrictions based on the efficient two-step GMM estimator. The p -value relating to the coefficient of $LSize(t-1)$ refers to the null hypothesis that its coefficient equals unity. $\hat{E}_{VC(\infty)}$ is the long-run effect of VC on firm size as given by Eq. (4) and computed by the Delta method. Standard deviations in round brackets, degrees of freedom in square brackets.

* $p < .10$.
 ** $p < .05$.
 *** $p < .01$.

Second, we checked whether survivorship bias in the data might affect our findings using the methodology described in Section 5.2. As is apparent from Table 7, the results of this test support the view that the findings presented in previous sections are not driven by survivorship bias.

Finally, we inserted in the set of explanatory variables in Eq. (1) two additional variables, $DSalariedManager_{i,t}$ and $DIPO_{i,t}$ (see Table 8). Previous studies suggest that two of the most important contributions of VC investors to portfolio firms are making it easier (i) to recruit professional managers (Hellmann and Puri, 2002; Bottazzi et al., 2008) and (ii) to go through an IPO and obtain additional financial resources (e.g. Puri and Zarutskie, 2008). Accordingly, $DSalariedManager$ is a dummy variable that switches

Table 8
Further evidence on the effect of VC investments on firm growth.

	Employees	Sales
$LSize(t-1)$	0.8252 (0.0521)***	0.7370 (0.0624)***
$LAge(t-1)$	-0.0357 (0.0401)	-0.1275 (0.0767)*
$DVC(t)$	0.3439 (0.0954)***	0.3378 (0.1224)***
$DSalariedManager$	0.2142 (0.0991)**	0.5828 (0.1424)***
$DIPO$	0.5681 (0.4708)	0.9125 (0.4104)**
Sector dummies	Yes	Yes
N	2953	2903
N groups	517	511
AR(1)	-8.43***	-6.11***
AR(2)	-0.70	1.60
Hansen test	133.84 [139]	117.66 [137]
$\hat{E}_{VC(\infty)}$	2.2230 (0.4974)***	1.2844 (0.4142)***

In 21 cases the exact year in which the first salaried manager was appointed by sample firms is unknown and hence we drop the firm from the sample. Out of the 21 dropped firms 10 are VC-backed. $DIPO$ is a dummy variable which switches to 1 when a company goes public. All estimates are based on a two-step system GMM model with robust standard errors and finite sample correction (Windmeijer, 2005). AR(1) and AR(2) are tests of the null hypothesis of respectively no first- or second-order serial correlation. Hansen is a test of the validity of the overidentifying restrictions based on the efficient two-step GMM estimator. Estimates in SYS-GMM columns are based on the hypothesis of DVC being endogenous, which implies their use as instruments since $t-2$ for the equations in first differences and $t-1$ for the equations in levels. The p -value relating to the coefficient of $LSize(t-1)$ refers to the null hypothesis that its coefficient equals unity. $\hat{E}_{VC(\infty)}$ is the long-run effect of VC on firm size as given by Eq. (4) and computed by the Delta method. Standard deviations in round brackets, degrees of freedom in square brackets.

* $p < .10$.
 ** $p < .05$.
 *** $p < .01$.

from 0 to 1 in the year in which the focal firm appointed the first professional salaried (i.e. non-owner) manager. $DIPO$ denotes listed firms. Addition of these variables to the model specification enables us to get further insights into the nature of the treatment effect of VC investments. While favoring listing of portfolio firms and making it easier to recruit professional managers, VC investments have a mediated positive effect on firm growth in addition to an autonomous direct effect which derives from the injection of finance in portfolio firms and other types of non-financial support. Results should be interpreted with caution owing to the limited number of sample firms that went through an IPO or appointed a professional salaried manager during the observation period (1% and 10% of the sample, respectively). Our estimates suggest that the effect of IPO on the growth of sample firms is limited to sales: the coefficient for $DIPO$, although positive in all estimates, is significant only in the sales equation. The appointment of a salaried manager has a positive impact that is statistically and economically significant on both employment growth and, especially, sales growth. Quite interestingly, the coefficients for the VC variable are lower than in the estimates with omission of the $DIPO$ and $DSalariedManager$ variables, especially in the sales equation, confirming the mediating role of these variables. However, these coefficients remain positive and significant. Therefore, our estimates suggest that there are several mechanisms through which VC investors positively influence the growth of portfolio firms, in addition to injecting finance.

7. Discussion and conclusions

7.1. Summary of results

The aim of this paper was to empirically analyze whether VC finance promotes the growth of NTBFs. In so doing, we wanted to isolate the *treatment* effect of VC investments on firm growth from the *selection* effect due to the ability of VC investors to pick firms with future high growth prospects which are unobserved by other investors (i.e. firms which would grow also in the absence of VC). We considered a longitudinal data set for a large sample of Italian NTBFs, most of which are privately held. The long longitudinal dimension of the data set and the availability of a rich set of firm-specific variables enabled us to estimate an augmented Gibrat-law-type dynamic panel-data model using several

estimation techniques that take into account the endogenous nature of VC finance.

Our results can be summarized as follows. First, VC investments have a large positive statistically significant treatment effect on the growth of employment and sales of NTBFs, over and beyond the effect attributable to selection. In particular, VC investments boost employment growth of portfolio firms in the period immediately after the first financing round. The estimated number of employees of a VC-backed firm at the end of the year following the first financing round is 110% larger than in the absence of VC. From year 2 after the first VC round, estimated employees continue to increase compared to growth in the absence of VC, but at a decreasing rate. The pattern is similar for what concerns sales growth: both the initial shock and the long run effect of the VC investment are statistically and economically significant, albeit they are lower than the ones for employment.

Second, the dynamic pattern and the magnitude of the treatment effect of VC investments on employment and sales are similar to those highlighted by Puri and Zarutskie (2008) for US privately held firms. Note, however, that the matching procedure used by these authors to compare VC-backed and non-VC-backed firms does not take into account unobservables that may drive both VC investments and VC-backed firms' future growth. Other studies (Sørensen, 2007; Chemmanour et al., 2008) claim that in the US there is a positive selection effect of VC investments. Therefore, the method used by Puri and Zarutskie (2008) probably overestimates the treatment effect of VC investments. As a corollary, the additional VC investors generate for portfolio firms is probably larger in Italy than in the US.

Third, differently from the above mentioned studies on the US, but in accordance with the limited evidence available on European VC-backed firms (Engel, 2002; Bottazzi et al., 2008; Colombo and Grilli, 2010a), we failed to detect any positive selection effect of VC investments. Our results indicate that, in Italy, VC investors do not pick "winners": they do not invest in firms that would grow also in the absence of VC. However, our study also clearly documents that VC is *not* a random treatment. VC investors are attracted by very young but relatively large firms. They also preferably invest in firms established by teams of individuals with university-level education in management and economics and prior managerial experience (see, also, Colombo and Grilli, 2010a). Again these findings largely replicate those of previous studies on US firms (see again Puri and Zarutskie, 2008. For qualitative evidence see e.g. Tyebjee and Bruno, 1984). Hence, while the *observable* characteristics of VC-backed firms are similar in Italy and in the US, *unobservable* characteristics that drive VC investments differ across the two countries.

7.2. Data limitations and additional qualitative evidence

The results illustrated above offer new original insights into the role of VC financing in fostering the growth of high-tech start-ups. However, we are aware that our study has some limitations that open new interesting directions for future research. First, in spite of the strengths of our dataset, the number of VC-backed firms included in our sample is rather limited. Therefore, in order to further check the robustness of our findings, it would be interesting to replicate the analysis on a larger sample of VC-backed firms. In addition, in accordance with the insights provided by previous studies (see e.g. Sørensen, 2007; Bottazzi et al., 2008), there may be substantial heterogeneity among VC investors according to characteristics such as investment experience and human capital of managing partners. There also are different types of VC investors: independent US-style VC investors, corporate VC, bank-affiliated VC, and governmental VC. They are likely to differ in the objectives they pursue, their organization, and their investment capabilities (see e.g. Gompers and Lerner, 2000; Hellmann, 2002). With a larger

sample, one could analyze whether these variables moderate the treatment effect (and the selection effect) of VC investments.

Second, we have documented that in an unfavorable environment such as the Italian economy, VC investments have a dramatic positive treatment effect on NTBF growth. Unfortunately, because of lack of data – notably, on the amount of finance received by VC-backed firms, we were not able to analyze the origin of this effect and in particular to assess whether it is mainly linked to an injection of finance or if it comes from other value enhancing activities performed by VC investors. We have shown in this study that the treatment effect of VC investments materializes immediately after the first VC round. This result indirectly suggests that the first injection of VC finance clearly is important to stimulate growth. However, our findings also suggest that VC investors bring more than financing to portfolio firms. Previous studies show that VC-backed firms are more likely than other firms to go through an IPO (e.g. Chang, 2004) and to recruit professional managers (Hellmann and Puri, 2002). In our dataset, only 5 firms went through an IPO during the observation period, 4 of which were VC-backed. Moreover, in a companion paper Colombo and Grilli (2010b) find that Italian VC-backed firms indeed more rapidly create a middle management level in their organization than their non-VC-backed peers. Our estimates indicate that these events positively affect firm growth and partially explain the positive treatment effect of VC investments. Moreover, Colombo and Grilli (2010a) find that the human capital characteristics of firms' founders that drive the growth of non-VC-backed firms lose all their explanatory power for VC-backed ones. This result is at odds with the view that an injection of finance is the only contribution VC investors provide to portfolio firms.

In order to shed additional light on this important issue, we collected qualitative evidence on the non-financial support VC-backed firms obtained from VC investors through face-to-face and phone interviews with the owner–managers of 22 VC-backed firms included in our sample. Almost three quarters of these firms (72.7%) declared that they received valuable "coaching" from their VC investors (score greater than 5 in a 7 points Likert scale). The areas in which VC investors provided the most valuable assistance were reputed to be accounting, budgeting and finance, corporate governance, and strategy formulation, which are also the areas in which entrepreneurs declared they were less competent. The majority of the entrepreneurs also asserted that after obtaining VC, their firms registered a significant improvement in the ease of access to external resources and capabilities, especially through the establishment of commercial alliances (see also Colombo et al., 2006), because of the certification effect of being VC-backed (77.3% of respondents attributed a score greater than 5 to this statement) and the network of business contacts (59.1% of the VC investor).¹⁶

Third, the absence of any positive selection effect of VC investments in our estimates also deserves further examination. Why is it that VC investors do not select the firms with the best (unobservable) future growth prospects? A possible explanation might be that, in Italy, most VC investors lack a "good nose" for talented entrepreneurs and successful business ideas. We think that this explanation, albeit possible in theory, is quite implausible, considering also the large positive treatment effect of VC. The support offered by VC investors in Italy and elsewhere, is especially valuable to firms that have large upside potential but cannot realize it due to lack of adequate competencies and resources (e.g. firms having a promising business idea which owner–managers are not able to develop autonomously). Conversely, this support is less precious

¹⁶ In this respect the advantage of being VC-backed is well summarized by the words of an entrepreneur that told us "The key advantage of being VC-backed resides in the ability of the VC investor to open doors that we could not open on our own".

to firms that may be able to establish a high-growth business also in the absence of VC. These latter firms will rationally self-select out of the VC market if the additionality provided by a VC investment is not large enough to offset the associated transaction costs. This event is more likely in Italy than in countries with a developed VC sector. First, the scarcity of VC supply in Italy, and notably the small number of reputable VC investors, increases the opportunity costs incurred by firms searching for VC. Second, the concentration of the VC market structure and the high market power of VC investors increase the “cost” of VC finance to candidate investee firms (i.e. the fraction of value enhancement which is internalized by VC investors rather than by incumbent shareholders). In the US, the number of VC investors is much larger and the supply of VC finance is more competitive than in Italy. Then, VC finance may be attractive even for firms with good autonomous growth prospects. A positive selection effect of VC investments follows. Clearly, these arguments are speculative. Getting a better understanding of the matching process between NTBFs and VC investors, and of the possible inefficiencies inherent in this process, figures prominently in our research agenda (see e.g. Bertoni et al., 2010b).

7.3. Policy implications

Our study has important policy implications. In all our econometric estimates, VC was found to have a large positive treatment effect on the growth performance of Italian high-tech start-ups. Our findings also indicated that the contribution of VC to firm performance is not exclusively attributable to an injection of finance, but coaching and other types of non-financial support VC investors offer to portfolio firms also play an important role. This evidence suggests that VC provides an important peculiar contribution to the creation of wealth in a knowledge-based economy, a contribution that cannot simply be obtained through public subsidies. As a corollary, our study argues in favor of the view that the development of a well-functioning VC sector should figure prominently in the policy agenda.

Indeed, in Europe, VC has been considered a priority by policy-makers for at least a decade now (see e.g. European Commission, 1999. See also Bertoni and Croce, 2011, for an analysis of recent policy measures in this area). So far, however, the results achieved are quite disappointing, especially in some countries (like Italy, as shown in Section 3).¹⁷ A detailed analysis of these policy failures is beyond the scope of the present work. However, our findings relating to the absence of any positive selection effect in our sample suggest that the matching process between VC investors and investee firms probably deserves a closer examination by policy makers.

Policies in European countries in this area have generally relied on two pillars. On the one hand, they have tried to increase the birth rate of innovative firms and consequently the demand for VC (i.e. the deal flow) through the provision of generous subsidies to young innovative companies and of fiscal advantages to their entrepreneurs. On the other hand, they have aimed at increasing also the supply of VC through co-investment schemes, the launch of new government-owned VC companies, and favorable

tax treatment of capital gains.¹⁸ While these measures clearly have some strengths, they may also have had some unexpected negative effects on the matching process between NTBFs and VC investors. As to fiscal policy, Keuschnigg and Nielsen (2002) show that an increase in the capital gains tax rate leads to greater incentives for VC investors to provide value-enhancing advice and services to investee companies. To the extent that this value-enhancement effort has a higher marginal benefit for firms with higher growth prospects, a decrease in the capital gain tax rate will discourage, rather than encourage, these firms to search for VC, thus making matching problems more severe. Moreover, the increase in the number of VC investors is instrumental to making the VC market structure more competitive and to reduce the transaction costs incurred by firms in searching for VC. However, if governmental VC investors lack the sophisticated skills of private VC investors (e.g. Brander et al., 2008), their entry into the VC market may create an adverse selection problem, thereby again inducing companies with high (unobservable) growth prospects to stay away from the VC market. This tendency may have been strengthened by the large availability of public subsidies, which makes the recourse to VC less compelling for these firms. Therefore, a reconsideration of the policy initiatives in this domain is in order in Europe. Our findings indicate that the design of policy schemes which attract high quality VC investors¹⁹ and at the same time induce NTBFs with future high growth prospects to look for external equity capital, is a crucial priority for European policy makers.

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Appendix A.

A.1. The RITA directory

The sample we use in this work was drawn from the 2004 release of the RITA (Research on Entrepreneurship in Advanced Technologies) directory. In principle, one would like to draw a representative sample from the population of Italian NTBFs that are

¹⁸ For instance, in France The *Jeunes Entreprises Innovantes* scheme gives tax exemptions and security payment release to young R&D intensive firms. Moreover, the recent *lois Tèpa* provides individuals who invest in young companies with a tax shield from the *Impôt sur les grandes fortunes* (tax on large wealth). On the supply side, CDC Entreprise, a subsidiary of *Caisse Dépôt et Consignation*, has been very active in promoting the launch of new government-supported VC funds, especially at regional level.

¹⁹ The Yozma program launched in Israel in the mid 1990s offers an example of this type of scheme. This program was a fundamental ingredient of the innovation policy that brought to the creation of a technology cluster in Israel (Avnimelech and Teubal, 2005). It included a co-investment scheme which provided VC investors with a strong upside incentive (i.e. a 5-years option to buy the government's share at cost). This incentive was designed to reward, and attract, higher-quality investors. Indeed, several reputable foreign VC firms entered the Israel market in the late 1990s.

¹⁷ The underdevelopment of the VC sector in Europe is somehow surprising, especially if one considers that the Private Equity (PE) sector, which includes all investment stages, flourished in Europe over the last decade. The size of the PE sector, in terms of investment amount, as a percentage of GDP was actually larger in Europe than in the US in 2009, but VC (defined as investments in the seed, start-up and expansion stages) accounted for only 17% of the European PE sector against 67% in the US (Source: European Venture Capital Association, EVCA; National Venture Capital Association, NVCA).

potential candidates for VC investment. Unfortunately, this is not possible for several reasons. First, in this domain, representativeness is a slippery notion because new ventures may be defined in different ways (see e.g. Aldrich et al., 1989). Second, national official statistics do not provide a reliable description of the population of Italian NTBFs. On the one hand, in Italy most individuals who are defined as self-employed by official statistics (i.e. “independent employees”) actually are salaried workers with atypical employment contracts. Unfortunately, on the basis of official data such individuals cannot be distinguished from owner–managers of a new firm. This means that the official number of NTBFs is enormously inflated, especially in sectors like software where atypical employment contracts are very popular. In addition, official data do not distinguish firms that were established by one or more entrepreneurs (i.e. owner–managed firms) from firms that were created as subsidiaries of other firms. This again inflates the number of NTBFs. Lastly, there are no official statistics about M&As: therefore one cannot distinguish firms that were acquired by another firm and lost independence while keeping their legal status, from independent NTBFs.

In absence of reliable official statistics, the RITA directory developed at Politecnico di Milano, presently is the most complete source of information on Italian NTBFs. The directory was created in 2000 and it was updated in 2002 and 2004. For its construction several sources were used. These included: (i) the lists of the companies that are members of the national entrepreneurial associations of the focal industries; (ii) the lists of the members of the regional sections of the Italian entrepreneurial association (Confindustria); (iii) the lists of the members of the local Chambers of Commerce; (iv) the lists of companies that participated in the most important industry trades and expositions; and (v) the lists of companies that purchased advertising services in popular off-line (e.g. Kompas) and on-line (e.g. Infoimprese.it) directories. Moreover, the RITA directory includes: (vi) the population of young firms that were granted by the Italian communication authority (AGCOM) a license to provide telecommunication services (including Internet access services), (vii) the population of NTBFs that were incubated in a science park or a business innovation centre (BIC) affiliated with the respective national associations, (viii) the population of NTBFs that obtained equity financing from VC investors that adhere to the Italian Venture Capital and Private Equity association (AIFI), and (ix) the population of VC-backed NTBFs that were included in VentureXpert. Lastly, information provided by the national financial press, specialised magazines, and other sectoral studies was also used in the compilation of the directory. Altogether, the 2004 release of the RITA directory comprises 1974 firms that complied with the criteria relating to industry of operations, age and independence mentioned in Section 4.1. For each firm, the name of a contact person (i.e. one of the owner–managers) is also provided. While the RITA directory obviously is not exhaustive of the population of Italian NTBFs, it provides the most extensive and accurate available coverage of this population. In particular, it is quite unlikely that potential candidates for VC investment are excluded from the RITA directory.

In the first semester of 2004, a questionnaire was sent to the contact person of the RITA directory firms either by fax or by e-mail. The first section of the questionnaire poses detailed questions relating to the human capital characteristics of firm’s founders. The second section comprises further questions concerning the characteristics of the firms including access to VC financing, the identity of VC investors, receipt of public subsidies, and the evolution over time of firm’s employees. Answers to the questionnaire were checked for internal coherence by educated personnel and were compared with information obtained from public sources (i.e. firm’s website and annual reports). In several cases, phone or face-to-face follow-up

interviews were made with firm’s owner–managers. This final step was crucial in order to obtain missing data and ensure that data were reliable.²⁰ In addition, financial and economic data including the evolution over time of firm’s sales from 1994 onwards, and data on patent activity during firm’s entire life were obtained from public sources (i.e. the AIDA and CERVED databases and the databases of patent offices, respectively). Data on VC financing was cross-checked with those available from public and commercial sources.

A.2. Orthogonality conditions implied by different GMM methods

(a) GMM-DIF

The Arellano–Bond GMM-DIF estimator overcomes the endogeneity problem inherited in a dynamic panel data model by employing an appropriate set of linear orthogonality conditions which depends crucially on the assumptions one is willing to make on the endogeneity, predetermined, or exogeneity of the explanatory variables. In this context, other than the lagged dependent variable, we make the weakest assumption possible and consider the VC financing variable as potentially endogenous. This means that the instruments we use starts from $t - 2$ both for the lagged dependent and the VC variable. In terms of orthogonality conditions and taking Eq. (1) as reference, this implies:

$$\begin{aligned} E(LSize_{i,t-s} \Delta \varepsilon_{i,t}) &= 0 \quad \text{for } t = 3, \dots, T \text{ and } s \geq 2 \\ E(VC_{i,t-s} \Delta \varepsilon_{i,t}) &= 0 \quad \text{for } t = 3, \dots, T \text{ and } s \geq 2 \end{aligned} \quad (1a)$$

(b) GMM-SYS

The GMM-SYS estimator enlarges the set of moment conditions used in the estimation. In particular, other than using lagged levels of the series as instruments for first differences equations, additional moment conditions are employed using first differences as instruments for variables in levels, starting from $t - 1$ for $\Delta LSize$ and for the ΔVC variables. These additional orthogonality conditions are:

$$\begin{aligned} E(W_i + \varepsilon_{i,t} \Delta LSize_{i,t-1}) &= 0 \quad \text{for } t = 3, \dots, T \\ E(W_i + \Delta \varepsilon_{i,t+1} \Delta VC_{i,t}) &= 0 \quad \text{for } t = 2, \dots, T \end{aligned} \quad (2a)$$

(c) Ahn and Schmidt (1995)

The estimator proposed by Ahn and Schmidt (1995) adds to the moment conditions carried by the DIF-GMM estimator an additional set of non-linear moment conditions. These $T - 2$ additional quadratic moment conditions are given by:

$$E(\varepsilon_{i,T} \Delta \varepsilon_{i,t+1}) = 0 \quad \text{for } t = 2, \dots, T - 1 \quad (3a)$$

A.3. Pseudo first-stage regressions

The orthogonality conditions shown above determine that lagged levels are used as instruments for difference equations and that lagged differences are used as instruments for level equations. The validity of these instruments has been verified by means of the Hansen test. However for these instruments to be good we have to verify that they are not weak. In order to do so we run the following pseudo–first-stage regressions:

$$\begin{aligned} \text{Difference: } \Delta DVC_{i,t} &= \alpha LSize_{i,t-2} + \sum_{\tau=t-2}^{t-6} \beta_{\tau} DVC_{i,\tau} + \gamma \Delta \ln(age)_{i,t} + \Delta \omega_{i,t} \\ \text{Levels: } DVC_{i,t} &= a \Delta LSize_{i,t-1} + \sum_{\tau=t-1}^{t-5} \beta_{\tau} \Delta DVC_{i,\tau} + \gamma \ln(age)_{i,t} + \eta_{i,t} \end{aligned}$$

²⁰ Note that only for 3 firms the set of owner–managers at survey date did not include at least one of the founders of the firm.

Table A1
Pseudo-first-stage regressions.

	Equations	Levels
	Difference	
$H_0 : \forall \tau : \beta_\tau = 0$	2.16**	1107***
Adj. R^2	0.011	0.806

The first line reports F statistics on the null Hypothesis of weak instruments.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

We then perform a Wald test on the null Hypothesis that all β coefficients in difference and all β coefficients in levels are jointly zero. The results are reported in the following table where we also report the adjusted R^2 of the pseudo-first-stage regression (Table A1).

Lagged instruments in first differences are strongly correlated with the VC variable, whereas oppositely, lagged instruments in levels are poorly correlated with the change in the VC-backing status, pointing to the strength other than the validity of the additional instruments used in the GMM-SYS estimates.

References

Ahn, S.C., Schmidt, P., 1995. Efficient estimation of models for dynamic panel data models. *Journal of Econometrics* 68, 5–27.

Aldrich, H.E., Kallenberg, A., Marsden, P., Cassell, J., 1989. In pursuit of evidence: sampling procedures for locating new businesses. *Journal of Business Venturing* 4, 367–386.

Aleman, L., Marti, J., 2005. Unbiased estimation of economic impact of venture capital backed firms. *EFA 2005 Moscow Meetings Paper*.

Amit, R., Brander, J., Zott, C., 1998. Why do venture capital firms exist? Theory and Canadian evidence. *Journal of Business Venturing* 13, 441–466.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58, 277–297.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-component models. *Journal of Econometrics* 68, 29–51.

Atanasov, V.A., Ivanov, V.I., Litvak, K., 2006. VCs and the expropriation of entrepreneurs. *SSRN Working Paper Series No. 905923*.

Audretsch, D.B., 1995. *Innovation and Industry Evolution*. MIT Press, Cambridge, MA.

Audretsch, D., Lehmann, E., 2004. Financing high-tech growth: the role of banks and venture capitalists. *Schmalenbach Business Review* 56, 340–357.

Avnimelech, G., Teubal, M., 2005. *Evolutionary Innovation and High Tech Policy: What can We Learn from Israel's Targeting of Venture Capital?* Neaman Institute, Technion, Science Technology and Economy Program, STE-WP25.

Baltagi, B.H., 2003. *Econometric Analysis of Panel Data*, 2nd edition. Wiley & Sons, Chichester, UK.

Barringer, B.R., Jones, F.F., Neubaum, D.O., 2005. A quantitative content analysis of the characteristics of rapid-growth firms and their founders. *Journal of Business Venturing* 20, 663–687.

Baum, J., Silverman, B., 2004. Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. *Journal of Business Venturing* 19, 411–436.

Benfratello, L., Sembenelli, A., 2006. Foreign ownership and productivity. Is the direction of causality so obvious? *International Journal of Industrial Organization* 24, 733–751.

Bertoni, F., Colombo, M.G., Croce, A., 2010a. The effect of venture capital financing on the sensitivity to cash flow of firm's investments. *European Financial Management* 16, 528–551.

Bertoni, F., D'Adda, D., Grilli, L., 2010b. Cherry Pickers or Frog Kissers? The Double Sided Matching Between Venture Capital and High-Tech Companies. 2010 Zvi Griliches Research Summer School in the Economics of Innovation, Barcelona.

Bertoni, F., Colombo, M.G., Croce, A., Piva, E., 2006. A review of the venture capital industry in Italy. In: Gregoriou, G.N., Kooli, M., Kraussl, R. (Eds.), *Venture Capital in Europe*. Elsevier, Amsterdam.

Bertoni, F., Croce, A., 2011. Policy reforms for venture capital in Europe. In: Colombo, M.G., Grilli, L., Piscitello, L., Rossi Lamastra, C. (Eds.), *Science and Innovation Policy for the New Knowledge Economy*, Edward Elgar.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* 87, 115–143.

Bond, S., 2002. *Dynamic panel data models: a guide to micro data methods and practice*. Portuguese Economic Journal 1, 141–162.

Bottazzi, L., Da Rin, M., 2002. Venture capital in Europe and the financing of innovative companies. *Economic Policy* 17, 229–269.

Bottazzi, L., Da Rin, M., Hellmann, T., 2008. Who are the active investors? Evidence from venture capital. *Journal of Financial Economics* 89, 488–512.

Brander, J.A., Egan, E.J., Hellmann, T., 2008. Government Sponsored versus Private Venture Capital: Canadian evidence. NBER Working Paper No. 14029.

Carpenter, R.E., Petersen, B.C., 2002. Capital market imperfections, high-tech investment, and new equity financing. *Economic Journal* 112, F54–F72.

Caves, R.E., 1998. Industrial organization and new findings on the turn-over and mobility of firms. *Journal of Economic Literature* 36, 1947–1982.

Chan, Y.S., 1983. On the positive role of financial intermediation in allocation of venture capital in market with imperfect information. *Journal of Finance* 35, 1543–1568.

Chang, S.J., 2004. Venture capital financing, strategic alliances, and the initial public offerings of Internet start-ups. *Journal of Business Venturing* 19 (5), 721–741.

Chemmanour, T.J., Krishnan, K., Nandy, D., 2008. How does venture capital financing improve efficiency in private firms? A look beneath the surface. Center for Economic Studies, U.S. Census Bureau Working Paper No. 08-16.

Chesher, A., 1979. Testing the law of proportionate effects. *Journal of Industrial Economics* 27, 403–411.

Colombo, M.G., Delmastro, M., Grilli, L., 2004. Entrepreneurs' human capital and the start-up size of new technology-based firms. *International Journal of Industrial Organization* 22, 1183–1211.

Colombo, M.G., Grilli, L., 2005. Founders' human capital and the growth of new technology-based firms: a competence based view. *Research Policy* 34, 795–816.

Colombo, M.G., Grilli, L., 2007. Funding gaps? Access to bank loans by high-tech start-ups. *Small Business Economics* 29, 25–46.

Colombo, M.G., Grilli, L., 2010a. On growth drivers of high-tech start-ups: the role of founders' human capital and venture capital. *Journal of Business Venturing* 25, 610–626.

Colombo, M.G., Grilli, L., 2010b. The creation of a middle-management level by entrepreneurial ventures: testing economic theories of organisational design. In: *DRUID Summer Conference 2009 Proceedings*.

Colombo, M.G., Grilli, L., Piva, E., 2006. In search for complementary assets: the determinants of alliance formation of high-tech start-ups. *Research Policy* 35, 1166–1199.

Cox, R.D., 1972. Regression models and life tables. *Journal of the Royal Statistical Society* 34, 187–220.

Da Rin, M., Nicodano, G., Sembenelli, A., 2006. Public policy and the creation of active venture capital markets. *Journal of Public Economics* 90, 1699–1723.

Davila, A., Foster, G., Gupta, M., 2003. Venture capital financing and the growth of start-up firms. *Journal of Business Venturing* 18, 689–708.

Delmar, F., Shane, S., 2006. Does experience matter? The effect of founding team experience on the survival and sales of newly founded ventures. *Strategic Organization* 4, 215–247.

Denis, D.J., 2004. Entrepreneurial finance: an overview of the issues and evidence. *Journal of Corporate Finance* 10, 301–326.

Eckhardt, J.T., Shane, S., Delmar, F., 2006. Multistage selection and the financing of new ventures. *Management Science* 52, 220–232.

Engel, D., 2002. The impact of venture capital on firm growth: an empirical investigation. Discussion Paper No. 02-02, Centre for European Economic Research (ZEW), Mannheim.

Engel, D., Keilbach, M., 2007. Firm level implication of early stage venture capital investment: an empirical investigation. *Journal of Empirical Finance* 14, 150–167.

European Commission, 1999. *Risk capital: a key to job creation in the European Union*. Discussion Report, Bruxelles, Belgium.

Feeser, H.R., Willard, G.E., 1990. Founding strategy and performance: a comparison of high and low growth high tech firms. *Strategic Management Journal* 11, 87–98.

Fischer, E., Reuber, R., 2003. Support for rapid growth firms: a comparison of the views of founders government policy makers and private sector resource providers. *Journal of Small Business Management* 41, 346–365.

Goddard, J., Wilson, J., Blandon, P., 2002. Panel tests of Gibrat's law for Japanese manufacturing. *International Journal of Industrial Organization* 20, 415–433.

Gompers, P.A., Lerner, J., 2000. The determinants of corporate venture capital success. In: Morck, R. (Ed.), *Concentrated Corporate Ownership*. University of Chicago Press, Chicago and London.

Gompers, P.A., Lerner, J., 2001a. The venture capital revolution. *Journal of Economic Perspectives* 15, 145–168.

Gompers, P.A., Lerner, J., 2001b. *The Money of Invention: How Venture Capital Creates New Wealth*. Harvard Business School Press, Boston.

Gorman, M., Sahlman, W.A., 1989. What do venture capitalist do? *Journal of Business Venturing* 4, 231–248.

Griliches, Z., 1992. The search for R&D spillovers. *Scandinavian Journal of Economics* 94, 29–47.

Groh, A., Liechtenstein, H., 2009. *The Global Venture Capital and Private Equity Country Attractiveness Index 2009/2010*. IESE Business School.

Hall, B., 2002. The financing of research and development. *Oxford Review of Economic Policy* 18, 35–51.

Hansen, L.P., 1982. Large sample properties of generalized method of moments estimators. *Econometrica* 50, 1029–1054.

Heckman, J., 1978. Dummy endogenous variables in a simultaneous equations system. *Econometrica* 46, 931–960.

Heckman, J., 1979. Sample selection bias as a specification error. *Econometrica* 47, 153–161.

Heckman, J., 1990. Varieties of selection bias. *American Economic Review* 80, 313–318 (papers and proceedings).

Hellmann, T., 2002. A theory of strategic venture investing. *Journal of Financial Economics* 64, 285–314.

- Hellmann, T., Puri, M., 2002. Venture capital and the professionalization of start-up firms: empirical evidence. *Journal of Finance* 57, 169–197.
- Hsu, D.H., 2006. Venture capitalists and cooperative start-up commercialization strategy. *Management Science* 52, 204–219.
- Huynh, K.P., Petrunia, R.J., 2006. Financial market imperfections: does it matter for firm size dynamics? SSRN Working Paper Series No. 879284.
- Ivanov, W., Xie, F., 2010. Do corporate venture capitalists add value to start-up firms? Evidence from IPOs and acquisitions of VC-backed companies. *Financial Management* 39, 129–152.
- Jain, B.A., Kini, O., 1995. Venture capitalist participation and the post-issue operating performance of IPO firms. *Managerial and Decision Economics* 6, 593–606.
- Jeng, L.A., Wells, P.C., 2000. The determinants of venture capital funding: evidence across countries. *Journal of Corporate Finance* 6, 241–289.
- Kaplan, S.N., Strömberg, P., 2003. Financial contracting theory meets the real world: an empirical analysis of venture capital contracts. *Review of Economic Studies* 70, 281–315.
- Kaplan, S.N., Strömberg, P., 2004. Characteristics, contracts and actions: evidence from venture capitalists analyses. *Journal of Finance* 59, 2177–2210.
- Keuschnigg, C., Nielsen, S.B., 2002. Tax policy, venture capital, and entrepreneurship. *Journal of Public Economics* 87, 175–203.
- Lee, L., 1983. Generalized econometric models with selectivity. *Econometrica* 51, 507–512.
- Lerner, J., 1995. Venture capitalists and the oversight of private firms. *Journal of Finance* 50, 301–318.
- Levin, A., Lin, C.F., Chu, C., 2002. Unit root test in panel data: asymptotic and finite sample properties. *Journal of Econometrics* 108, 1–25.
- Lindsey, L., 2008. Blurring firm boundaries: the role of venture capital in strategic alliances. *Journal of Finance* 63, 1137–1167.
- Lockett, A., Murray, G., Wright, M., 2002. Do UK venture capitalists still have a bias against investments in new technology firms? *Research Policy* 31, 1009–1030.
- Maliranta, M., 2005. R&D, international trade and creative destruction: empirical findings from Finnish manufacturing industries. *Journal of Industry, Competition and Trade* 5, 27–58.
- Manigart, S., Van Hyfte, M., 1999. Post-investment evolution of venture backed companies. In: Reynolds, P., Bygrave, W., Manigart, S., Mason, C., Meyer, G., Sapienza, H.J., Shaver, K. (Eds.), *Frontiers of Entrepreneurship Research*. Babson College, Wellesley, MA.
- Masulis, R.W., Nahata, R., 2009. Venture capital conflicts of interest: evidence from acquisitions of venture backed firms. ECGI Finance Working Paper No. 211/2008.
- Puri, M., Zarutskie, R., 2008. On the lifecycle dynamics of venture-capital- and non-venture-capital-financed firms. CES Working Paper No. 08-13.
- Rajan, R., Zingales, L., 2003. The great reversals: the politics of financial development in the twentieth century. *Journal of Financial Economics* 69, 5–50.
- Revest, V., Sapio S., forthcoming. Financing technology-based small firms in Europe: what do we know? *Small Business Economics*.
- Sapienza, H.J., 1992. When do venture capitalists add value? *Journal of Business Venturing* 7, 9–27.
- Sapienza, H.J., Manigart, S., Vermeir, W., 1996. Venture capital governance and value added in four countries. *Journal of Business Venturing* 11, 439–469.
- Schoenfeld, D., 1982. Residuals for the proportional hazards regression model. *Biometrika* 69, 239–241.
- Semykina, A., Wooldridge, J.M., 2010. Estimating panel data models in the presence of endogeneity and selection. *Journal of Econometrics* 157, 375–380.
- Stuart, T.E., Hoang, H., Hybels, R., 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative Science Quarterly* 44, 315–349.
- Sutton, J., 1997. Gibrat's legacy. *Journal of Economic Literature* 35, 40–59.
- Sørensen, M., 2007. How smart is smart money? A two-sided matching model of venture capital. *Journal of Finance* 62, 2725–2762.
- Tyebjee, T.T., Bruno, A.V., 1984. A model of venture capitalist investment activity. *Management Science* 30, 1051–1066.
- Ueda, M., 2004. Banks versus venture capital: project evaluation, screening, and expropriation. *Journal of Finance* 59, 601–621.
- Vella, F., Verbeek, M., 1999. Estimating and interpreting models with endogenous treatment effects. *Journal of Business and Economic Statistics* 17, 473–478.
- White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48, 817–830.
- Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics* 126, 25–51.
- Winship, C., Morgan, S.L., 1999. The estimation of causal effects from observational data. *Annual Review of Sociology* 25, 659–706.
- Wooldridge, J.M., 1995. Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics* 68, 115–132.
- Wooldridge, J.M., 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, USA.