What money cannot buy: a new approach to measuring venture capital value added

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ABSTRACT

In this work, we present evidence on the impact of venture capitalists' value added on investee's performance based on a new approach. Whilst most of the literature compares venture capital (VC)-backed companies with similar companies that did not receive external financing, in this paper we also compare VC-backed firms with similar companies that received external quasi-equity financing (in the form of participative loans) but not value-adding services. We use a difference-in-difference-in-difference (DDD) estimator to isolate the contribution of the value added by the VC firm and disentangle it from the effect derived from the injection of financial resources. Starting from the populations of Spanish companies that received either VC (830) or participate loans (929) between 2005 and 2011, and 14,111 companies that received neither, we find that VC-backed companies have a significantly higher growth in employees, total assets and (less significantly) sales than those receiving participative loans, arguably due to VC value added. Moreover, we show that the value brought about by VC is driven by VC firms with more capital under management, with broader experience and with a lower number of companies to oversee per portfolio manager. Our results are robust to alternative methodologies that control for endogeneity.

Keywords: *Venture capital, participative loans, value added, performance.*

1. Introduction

Venture capital (VC) investors have attracted substantial academic interest for their ability to provide more than just money to portfolio companies. VC involvement is characterized by a complex bundle of value-adding activities, such as coaching and professionalization, which are not present in other forms of external finance (Gorman and Sahlman, 1989; Kaplan and Strömberg, 2004; Lerner, 1995; Sapienza et al., 1996). As highlighted by Croce et al. (2013), the extent to which these value-adding activities have actually an impact on investee firm's performance is still a pending research question. In this paper, we propose a novel approach to address this issue, and provide evidence on the conditions under which VC investors are able to add value to their portfolio companies.

There is overwhelming evidence that companies that receive VC perform better than non-VC-backed companies. VC-backed companies outperform non-treated companies across many dimensions, such as innovation (Hellmann and Puri, 2000; Kortum and Lerner, 2000), employment growth (Bertoni et al., 2011; Grilli and Murtinu, 2014), sales growth (Engel and Keilbach, 2007), productivity (Chemmanur et al., 2011; Croce et al., 2013; Croce and Martí, 2016) and survival (Timmons, 1994). However, the higher performance of VC-backed companies does not necessarily mean that VC investors 'add value'.

First, VC-backed companies may perform better because they are systematically different with respect to other companies, even before the VC funding ('selection' effect). In fact, VC investors carefully analyze the growth potential and promising business opportunities of the companies applying for VC finance (screening process) and select only the most promising ones (Amit et al., 1998; Chan, 1983). Second, the higher performance of VC-backed firms could be (at least partially) attributable to the fact that VC investors are injecting financial resources in companies that are financially constrained. Such injection allows companies to undertake investments opportunities they would otherwise forgo, thus showing better performance.

Many efforts have been made by scholars to understand to what extent the better performance of VC-backed companies is due to their implicit higher value ('screening' effect), to the relaxation of financial constraints ('funding' effect) or to VC value-adding services ('value-added' effect).

In most cases, scholars focused on disentangling 'selection' and 'value-added' effects. The impact of VC value added is often estimated by comparing the post-investment performance of VC-backed companies with that of companies that are similar but that did not receive VC. Selection effects are usually accounted for through a matching procedure before the first round of VC funding. Since unobservable factors may affect both VC selection and post-investment performance, some papers also rely on instrumental variables and two-stage estimation methodologies to address VC endogeneity (e.g., Croce et al., 2013).

We argue that these approaches overestimate the effect of VC value added by not properly accounting for the ‘funding’ effect of VC. In most papers, the effect of funding is accounted for by including the total VC amount received by the investee firm in the control variables (e.g., Grilli and Murtinu, 2014). However, an injection of financial resources in a financially constrained company may lead to a structural change in the way in which a company operates, as it allows for instance companies to invest in fixed assets or hire skilled workers. These assets can substantially improve the performance of a VC-backed company, even in absence of any value added by VC.

Hence, whether the higher performance of VC-backed firms is attributable to value added or to the fact that VC investors are injecting financial resources into promising companies that are financially constrained is still an open question. To the best of our knowledge, there is no contribution that specifically isolates the impact on performance of value added from the effect of funding related to VC involvement.

We aim to fill this gap by proposing a different and novel empirical approach. Instead of simply comparing the performance of VC-backed and similar non-VC-backed firms, we also analyze the performance of companies that received long-term external finance after careful screening. We focus on the case of participative loans (hereafter, PLs), which are hybrid instruments used by governmental agencies. Like VC, PLs are a form of long-term finance (quasi-equity) awarded after a detailed screening process. However, unlike VC, the institution granting the PLs does not provide any value-adding services and monitoring. Thus, we compare the performance of three groups of companies: *a)* VC-backed companies (they receive funding and value-adding services); *b)* similar PL-backed companies (they receive only funding, without any value-adding services) and *c)* similar non-treated companies. Such approach allows us to isolate the contribution of the value added by VC firms from the mere effect derived from the injection of long-term financial resources in promising companies. Specifically, we use a 'difference-in-difference-in-difference' (DDD) estimator to test whether VC investors add value to their portfolio ventures, and also to identify the drivers of such ability. We keep selection effects fixed by adopting a matching approach, and we also use alternative methodologies to control for endogeneity.

We test our hypotheses on a sample of Spanish companies extracted from the Webcapitalriesgo database. Such database has the advantage of collecting information on the population of VC-backed and PL-backed companies in Spain, and on a massive control group. Moreover, it contains detailed information on the VC investors, which is usually not available in secondary datasets, including capital under management, experience, and number of portfolio firms per VC manager.

Our paper contributes to the literature by being, as far as we know, the first one in testing the value added by VC firms by directly and explicitly disentangling the impact of funding from the effect derived from the value-adding services provided to investee companies. Furthermore, we provide evidence on which characteristics drive the VC investor's ability to add value, focusing on VC firm size, experience, and attention to portfolio companies.

The structure of the paper is as follows. In Section 2 we present the theoretical background. In Section 3 we present the data and the methodology used. We show our results in section 4. Finally, in section 5 we discuss our findings and conclude.

2. Theoretical background

2.1 External equity finance: the case of VC

According to the agency costs theory (Jensen and Meckling, 1976), information asymmetries between shareholders and managers introduce an agency problem that may affect a firm's investment and financing decisions. Information asymmetries are exacerbated in entrepreneurial ventures. Even with a superior business concept and management team, these ventures fail to communicate the appropriate information to potential investors and, as a consequence, experience serious difficulties in raising funds (Binks et al., 1992). The low value of collateral is an additional deterrent for commercial banks and other debt providers to bear the high risk of investments in young entrepreneurial ventures (Berger and Udell, 1990). As a result, many entrepreneurial companies exclusively resort to internal finance to fund their investment projects (Carpenter and Petersen, 2002a) and thus forgo their growth opportunities when external finance is also required (Bertoni et al., 2013, 2010).

Equity capital may represent a good financing alternative for entrepreneurial ventures, as it does not require collateral, it does not increase the probability of financial distress and the investors' upside returns are not bounded (Carpenter and Petersen, 2002b). VC investors are prominent equity providers for entrepreneurial ventures (Hellmann and Puri, 2000; Kortum and Lerner, 2000). These financial intermediaries are able to reduce problems associated with information asymmetries in several ways. They perform a detailed screening process (Amit et al., 1998; Chan, 1983). They sign contracts to oversee and incentivize portfolio company managers (Admati and Pfleiderer, 1994) and conduct a close supervision and monitoring of portfolio firms after investment (Fiet et al., 1997; Lerner, 1995; Mitchell et al., 1997). Previous evidence documents that the injection of financial resources provided by VC investors results in VC-backed entrepreneurial ventures being less financially constrained (Bertoni et al., 2013, 2010) and eventually more able to prosper and grow (Carpenter and Petersen, 2002b; Davila et al., 2003). Therefore, we expect that entrepreneurial ventures receiving VC (i.e., VC-backed companies) will perform better than similar companies that did not receive external finance, because of the injection of financial resources and the consequent relaxation of financial constraints. However, such effect may take place for other forms of external finance as well, as long as they are provided to promising entrepreneurial ventures after careful screening.

2.2 VC firm's value added

As Colombo and Grilli (2010) emphasize, the agency costs theory neglects to take into consideration that VC firms also perform a key coaching function, largely beyond pure monitoring. In fact, besides providing capital, VC investors usually sit on the board of directors of their portfolio companies and are actively involved in their development and organization (Gorman and Sahlman, 1989; Sahlman, 1990). Therefore, the agency costs theory alone does not provide sufficient support to the evidence on the outperformance of VC-backed firms.

Since VC managers provide a wide range of value-adding services, well beyond pure monitoring, Croce et al. (2013) argue that the resource-based view of the firm (Penrose, 1959; Wernerfelt, 1984) adds to the agency theory in explaining the outperformance of VC-backed companies. The existence of imperfect markets is understood to be a critical element in explaining how resources generate competitive advantages. Hence, the access to valuable resources (i.e., those that are difficult to trade or imitate on the spot market) is an important driver of firm performance (Barney, 1991; Ireland et al., 2003). VC investors provide portfolio companies with both valuable financial and nonfinancial resources.

Few papers tried to classify the evidence on the nonfinancial value-adding activities of VC investors (Large and Muegge, 2008; Luukkonen et al., 2013; Proksch et al., 2017). Three groups of value-adding activities related to VC are typically identified. First, VC firms directly add value to investees by performing a 'coaching' function, that is, providing them with financial, administrative, marketing, strategy and management support (Gorman and Sahlman, 1989; Lerner, 1995; Sahlman, 1990; Sapienza et al., 1996; Sapienza, 1992; Sørensen, 2007),[1] which is deemed to be especially useful for young innovative firms operating in high-technology sectors (Bygrave and Timmons, 1992; Kaplan and Strömberg, 2004; Sapienza et al., 1996). Second, VC fosters the managerial 'professionalization' of this type of firms (Bottazzi et al., 2008; Hellmann and Puri, 2002), establishes alliances with third parties and facilitates access to specialized

[1] Although there is also evidence against this function (e.g., see Busenitz et al., 2004).

professional services (Colombo et al., 2006; Hsu, 2006; Lindsey, 2008). Third, VC investors signal the quality of the portfolio firms to third parties such as customers, alliance partners, skilled workers, banks and other financial intermediaries (Stuart et al., 1999). Since the value-adding activities are unique to VC investments and are not provided automatically by other forms of selective long-term financing, we posit the following hypothesis.

Hypothesis 1. *VC-backed companies will outperform companies that received other forms of selective long-term finance which do not entail value-adding services.*

2.3 Drivers of VC value added

Previous research suggests that there is a high heterogeneity across VC firms, and not all VC investors have the same ability to add value to portfolio companies (Dimov and Shepherd, 2005; Drover et al., 2017; Kaplan and Schoar, 2005; Sørensen, 2007). Specifically, we highlight three main VC characteristics, previously identified in the literature, which moderate value added: the size of the VC firm, the experience of VC managers, and the degree of attention devoted to portfolio companies.

Regarding VC firm size, Burgel and Murray (2000) argue that VC firms with a sizable amount of capital under management benefit from substantial scale economies, particularly in the accessing and utilization of project-specific information employed in the initial appraisal, due diligence, valuation and monitoring of portfolio investments (Murray and Marriott, 1998; Tyebjee and Bruno, 1984; Westhead and Storey, 1997). Moreover, large VC funds have better connections and may have access to a broader network of contacts (Humphery-Jenner, 2012), which allows them to hire better professionals able to more effectively manage and add value to portfolio companies.[2] Following these arguments, we state our second hypothesis as follows.

Hypothesis 2. *The outperformance of VC-backed companies, with respect to other companies that received selective long-term finance without value-adding services, will be higher for those backed by VC investors with more capital under management.*

As regards the role of VC manager's experience on investee firm's performance, more experienced VC firms can influence and add value to companies in several ways (Sørensen, 2007). First, more experienced VC investors may be better at monitoring and managing the uncertainty surrounding entrepreneurial ventures (Dimov and Shepherd, 2005). Second, they may have access to larger networks, drawing on a greater number of contacts with suppliers, customers, and potential managers (Hellmann and Puri, 2002; Hochberg et al., 2007). Third, the reputation of an experienced VC firm may communicate unobserved qualities about the company to the market, thus positively impacting on its market value (Megginson and Weiss, 1991). Based on their skills in managing different firms, more experienced VC firms are in a better position to deploy governance mechanisms that will lead to better performance (Busenitz, 2007). Reinforcing these arguments, Meuleman et al. (2009) find that higher levels of private equity firm experience are associated with higher levels of growth in the buyout company, while Sørensen (2007) find that companies funded by more experienced VC investors are more likely to go public. In the same vein, and based on a major survey of about 300 independent VC investors, combined with face-to-face structured interviews, De Clercq and Fried (2005) document that the experience of the VC managers is perceived to have a substantial influence on

[2] Nevertheless, the extant literature also highlights that there is an optimal fund size (Cumming and Dai, 2011; Fulghieri and Sevilir, 2009; Humphery-Jenner, 2012; Kaplan and Schoar, 2005), as very large funds could neglect to provide valuable support in the case of extremely large portfolios. For that reason, we also consider the attention devoted by VC firms to their portfolio companies as an additional driver for value added.

how effective VC firm's contributions towards their investee companies are, and ultimately affect the performance of these companies. Therefore, we posit the following hypothesis:

Hypothesis 3. *The outperformance of VC-backed companies, with respect to other companies that received selective long-term finance without value-adding services, will be higher for those backed by more experienced VC investors.*

Finally, regarding the attention devoted by VC investors to their portfolio companies, the number of investee companies is also likely to influence the constructive coaching and value provided by VC managers because of the resulting division of time, attention and resources (Fulghieri and Sevilir, 2009). Jääskeläinen et al. (2006) find that the attention devoted by VC managers to investee firms is a key driver of their performance. One of the measures used in the literature to analyze the extent to which VC investors are able to devote attention to portfolio companies is the ratio between the number of portfolio companies and the number of venture managers overseeing them (Balboa and Martí, 2007; Cumming, 2006). A high number of portfolio companies per VC manager tends to undermine the quality of advice (Bernile et al., 2007; Kanniainen and Keuschnigg, 2003). Reinforcing this idea, De Clercq and Fried (2005) find that the effectiveness of the VC firm’s assistance and the performance of investee firms are dependent on the effort and commitment of VC managers. Based on the previous arguments, our fourth hypothesis is stated as follows.

Hypothesis 4. *The outperformance of VC-backed companies, with respect to other companies that received selective long-term finance without value-adding services, will be higher for those backed by VC investors with a lower number of companies to oversee per portfolio manager.*

3. Methodological approach and Data

3.1 PLs as a selective quasi-equity long-term source of finance

PLs are a hybrid form of long-term external finance which shares common aspects with both loans and equity. PLs have pre-determined maturity and interest payments, which are divided into two components. The first one is independent of the company's performance and is usually determined by the reference interest rate (e.g., Euribor) plus a spread. The second one is performance-contingent, as it is based on the company's profits (i.e., net profit) in the relevant year. In order to be eligible to obtain a PL, applicants must go through a thorough screening process that assesses the viability and innovativeness of the business plan and the professionalization of the management team.

PLs attracted substantial attention from policymakers interested in filling the financing gap left by private investors, including VC. In fact, VC firms invest in only a very limited number of the most promising companies (Sahlman, 1990), thus leaving many entrepreneurial ventures unfunded. Since these companies strongly contribute to value creation and employment, policymakers have designed a variety of schemes to directly allocate public funding to entrepreneurial ventures. Recently, they have directed their attention towards hybrid instruments, including PLs (OECD, 2015).

On the one hand, because of their quasi-equity nature and the fact that they are provided after careful screening, PLs are comparable to VC as a form of external (quasi) equity financing. Similar to VC, PLs represent then an injection of long-term finance in selected promising companies that are financially constrained. In addition, beneficiary firms are also able to increase long-term funding from banks (Martí and Quas, 2017). Hence, the receipt of PLs should unleash companies' potential and foster their subsequent performance (Carpenter and Petersen, 2002a). Supporting this idea, Bertoni et al. (2017) show that PLs significantly boost the growth of employees of beneficiaries in a sample of 521 firms that received a PL from a Spanish government institution between 2005 and 2011.

On the other hand, the entity granting PLs does not have a say in the way in which the awarded companies are managed. Therefore, unlike VC, PLs do not entail any value-adding services. Hence, PLs represent an appropriate counterfactual for testing our hypotheses about the non-financial value added by VC investors to their portfolio companies.

3.2 Empirical approach

In our analysis, we first resort to two difference-in-difference (DD) estimators to compare VC-backed and PL-backed firms with untreated firms. The DD estimator is quite common in the VC literature (for a recent application, see Bernstein et al., 2016). It is computed as the difference in the dependent variable of interest (in our case, the investee company's performance) around the year t in which a treatment (VC or PL financing) is introduced for treated companies, and then compare this difference with the difference around the same year t for non-treated companies (companies that never received VC/PLs but that otherwise present similar characteristics). The DD estimator is the difference between the two differences and is the estimated effect of the treatment on the treated (i.e., the effect of VC/PLs on the invested company's performance).

In the case of the sample of VC-backed companies, we argue that the DD estimator jointly captures the effect of both funding and value added on performance, whereas in the case of the sample of PL-backed companies performance will be only based on the funding provided.

Since our aim is to isolate the improvement in performance not due to the injection of financial resources but solely to the value added by VC investors, we adopt a difference-in-difference-in-difference (DDD) approach (Imbens and Wooldridge, 2007), which consists in estimating the effect of VC value added as the difference between two DD estimators. So, we add a third level of differences by computing the difference in time and across two groups for two different treatment variables: VC and PLs. In our approach, we first compute the DD estimator for both VC and PLs with respect to a control group, and then we compute the difference between the two DD estimators to generate the DDD estimator. This difference should be positive. It measures by how much the VC treatment improves company's performance more than what the PL treatment does, because of the value added provided by VC managers.[3]

3.3 Sample selection

In order to implement our empirical approach, we build a dataset in which three groups of companies are considered: VC-backed companies, PL-backed companies and untreated (i.e., control group) companies. Ideally, companies in these three groups should have similar characteristics and only differ for the presence and type of treatment they receive.

To build such a dataset, we begin by considering the population of VC-backed companies in Spain. Specifically, we rely on the Webcapitalriesgo database, which contains information on the population of VC-backed companies located in Spain. Webcapitalriesgo is the service provider that produces the official statistics of the Spanish Private Equity and Venture Capital Association (ASCRI). We extracted from this database information on all companies that

[3] An important assumption of our approach is that the effects of the injection of financial resources of PLs and VC are similar. We believe this is the case because both VC and PLs share the equity-like form of financial injection and are comparable in terms of amount committed (see statistics below), and the usual duration of the PL is at least as long as the average holding period in VC investments. Additionally, VC-backed and PL-backed companies also share common characteristics: they both actively looked for external financing, and were both selected by external investors after a careful screening of their potential.

received the first round of VC financing between 2005 and 2011, identifying those that were founded between 1996 and 2010, when they were up to 10 years old. This population consists of 830 companies.

For PL-backed companies, we used the population of 929 companies that were awarded with their first participative loan (PL) by either Empresa Nacional de Innovación (hereinafter, ENISA) or INVERTEC (governmental program from the regional government of Catalonia) between 2005 and 2011 and were founded between 1996 and 2010, when they were up to 10 years old. The data were provided by both institutions and confronted with Webcapitalriesgo.

We discarded 223 companies that received both VC and PLs to be able to isolate the effect of VC from that of PLs, thus leading to a reduction in the respective populations to 706 PL-backed companies and 607 VC-backed companies.[4]

We also identified a huge sample of companies that received neither VC nor PLs (i.e., non-treated firms). We have information on 14,111 non-treated companies, founded between 1996 and 2010. These companies were randomly extracted from Orbis in a sequential process where age, regions, and activity sectors were used as stratifying variables.

In order to ensure comparability of the VC-backed, PL-backed and control group companies, we extracted some matched samples from the populations described above. Specifically, we use two Propensity Score Matching (PSM) 1:1 algorithms without replacement using the following variables: a) age (Age_t); b) logarithm of gross revenues plus 1 ($lnSales_t$); c)

[4] In the robustness check presented in section 4.4, companies that received both VC and PL are not excluded from the analysis.

logarithm of cash available plus 1 (*lnCash*$_t$); d) percentage of intangible assets on total assets (*Intangibles*$_t$), industry, region and year dummies.[5]

First, we matched VC-backed companies in the year before the initial VC financing round with PL-backed companies in the year before the first PL was granted. We successfully matched 222 VC-backed companies with 222 PL-backed firms. We then matched the 222 selected VC-backed companies in the year before the VC funding with all observations for non-treated companies, finding 215 twins. This leaves us with 659 companies: 222 VC-backed, 222 PL-backed and 215 non-treated peers. Table 1 below shows the distribution of sample companies by type, industry, region and foundation period, both before and after the matching algorithm.

Before matching, within the population of 830 VC-backed companies, the activity sectors showing a larger share of investees are professional services, software, and R&D services. Within the population of 929 PL-backed companies, we find a stronger tendency to operate in software, professional services, and trade services. In terms of regions, VC-backed companies are more concentrated in Andalusia, Catalonia, and the Madrid region whereas PL-backed companies also show a concentration in the same three regions, albeit in a different order: Catalonia, Madrid, and Andalusia. The largest share of both VC-backed and PL-backed companies was founded between 2006 and 2011 but the former were more likely than the latter to be established during the 2001-2005 period.[6] The 223 companies excluded because they received both VC and PLs were more concentrated in Catalonia and Madrid and mostly focused on high-technology sectors.

[5] Alternative matching algorithms are discussed in section 4.3. We treat the potential endogeneity of VC and PLs treatments, due to unobservable characteristics, in section 4.4.
[6] These statistics are computed for the whole population of VC-backed and PL-backed companies, also including those firms that received both VC and PL.

After the matching process, the distributions of the three groups are not significantly different at standard significance levels for industry ($\chi^2(18)$= 14.27), regions ($\chi^2(24)$= 28.87) and foundation periods ($\chi^2(4)$= 5.40). Table 2 shows descriptive statistics in the year of the matching on the matching variables for the three groups of matched companies. Some ANOVA tests indicate that there are no significant differences across groups for age (Age_t, F(2)= 1.59), size ($lnSales_t$, F(2)= 24.09), liquidity ($lnCash_t$, F(2)= 0.05) and intangibles ($Intangibles_t$, F(2)= 1.72). This result confirms the balancing of the matching.

Table 1: Distribution of matched VC-backed, PL-backed and non-treated firms by industry, region and foundation period

	All companies					Matched companies			
Treatment	Only VC*	Only PL*	Both	None	Total	Only VC	Only PL	None	Total
Distribution by industry									
Manuf. of chemicals incl. pharmaceuticals and materials	45	26	13	1,209	1,293	15	18	10	43
Manuf. of computers and equipment	33	40	14	441	528	7	5	3	15
Other manufacturing[1]	39	52	16	1,162	1,268	15	12	19	46
Trade services	51	100	18	2,008	2,177	24	39	26	89
ICT services	36	67	15	194	312	16	19	19	54
Professional services	104	103	25	1,653	1,885	42	32	37	111
Software	75	123	51	1,381	1,630	33	39	33	105
R&D services	74	44	46	803	967	29	26	26	81
Other Services[2]	93	118	15	2,416	2,642	26	21	25	72
Other low technology sectors[3]	57	33	10	2,844	2,944	15	11	17	43
Total	*607*	*706*	*223*	*14,111*	*15,646*	*222*	*222*	*215*	*659*
Distribution by region									
Andalusia	210	86	20	2,623	2,939	60	42	67	169
Aragon	21	20	15	525	581	11	10	9	30
Asturias	30	14	3	305	352	7	3	6	16
Castile- La Mancha	11	20	5	387	423	3	1	2	6
Castile-Leon	18	14	7	427	466	6	6	6	18
Catalonia	79	183	73	2,969	3,304	35	58	36	129
Valencian Community	19	43	12	1,087	1,161	9	8	6	23
Extremadura	34	11	5	347	397	7	4	6	17
Galicia	30	34	4	882	950	14	14	7	35
Madrid	70	197	43	2,416	2,726	35	44	32	111
Murcia	3	22	1	299	325	1	3	0	4
Navarra	20	14	11	257	302	8	9	7	24
Basque Country	56	33	16	921	1,026	26	20	31	77
Others	6	15	8	666	695	0	0	0	0
Total	*607*	*706*	*223*	*14,111*	*15,647*	*222*	*222*	*215*	*659*
Distribution by foundation period									
1996-2000	26	39	7	2,880	2,952	22	13	19	54
2001-2005	198	182	78	5,411	5,869	96	88	98	282
2006-2011	383	485	138	5,820	6,826	104	121	98	323
Total	*607*	*706*	*223*	*14,111*	*15,647*	*222*	*222*	*215*	*659*

[1] Other manufacturing includes manufacturing of food products, beverages and tobacco products; manufacturing of textiles, apparel, leather and related products; manufacturing of wood and paper products, and printing. [2] Other services include transportation and storage, and accommodation and food service activities. [3] Other low technology sectors include agriculture, forestry, fishing, mining, and quarrying.

* This column reports companies that received only VC or PLs. The full population of VC-backed or PL-backed companies is the result of the sum of the respective column and the column *Both*, which reports companies that received both VC and PLs.

Table 2: Descriptive statistics by group in the year of the matching

	N	Mean	Std. Dev.	Min	Max
VC-backed companies					
Age_t	222	2.095	2.168	0.000	9.000
$lnSales_t$	222	10.232	4.504	0.000	20.877
$lnCash_{t-1}$	222	10.394	2.768	0.000	18.767
$Intangibles_{t-1}$	222	0.169	0.243	0.000	0.972
PL-backed					
Age_t	222	1.932	2.161	0.000	9.000
$lnSales_t$	222	10.027	4.763	0.000	17.131
$lnCash_{t-1}$	222	10.320	2.607	0.000	15.607
$Intangibles_{t-1}$	222	0.212	0.256	0.000	0.924
Non treated					
Age_t	215	2.312	2.352	0.000	9.000
$lnSales_t$	215	10.677	3.745	0.000	17.354
$lnCash_{t-1}$	215	10.339	1.910	4.293	15.972
$Intangibles_{t-1}$	215	0.178	0.267	0.000	0.908
Total					
Age_t	659	2.111	2.230	0.000	9.000
$lnSales_t$	659	10.308	4.367	0.000	20.877
$lnCash_{t-1}$	659	10.351	2.458	0.000	18.767
$Intangibles_{t-1}$	659	0.186	0.256	0.000	0.972

Age_t is measured in years. $lnSales_t$ *is* equal to the logarithm of gross sales plus 1. $lnCash_{t-1}$ is the logarithm of cash available plus 1, lagged by one year. $Intangibles_{t-1}$ is the percentage of intangible assets on total assets, lagged by one year.

3.4 Model specification

Following a common procedure in the extant literature (e.g., Bertoni et al., 2011; Puri and Zarutskie, 2007), we focus on growth to test the impact of VC value added on the performance of target companies. Specifically, we estimate the growth of sales, employment and total assets with some fixed effects models whose dependent variables are $lnSales_t$, $lnEmployees_t$ and $lnTotalAssets_t$, respectively, equal to the logarithm of gross sales, the number of employees, and total assets of companies, plus 1. In each model, we control for company age (*Age*), liquidity (*lnCash*), intangibles as a share of total assets (*Intangibles*) and time periods.

We use several independent variables to capture the treatment effect associated with VC and PLs. VC_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC, lagged by one year. Similarly, PL_{t-1} turns from 0 to 1 in the year in which a company receives its first PL, and is lagged by one year. The coefficients of these variables will represent the DD estimators of the treatment effects of VC and PLs on companies' performance. The difference between the two coefficients will represent the DDD estimator of interest in this study, which should capture the effect of the value added brought about by VC and not present for PLs, according to Hypothesis 1. To better isolate the value-adding effect from the effect of the mere injection of financial resources, we also include information on the amount of VC and PL funds received by the focal company in the regressions. $lnAmount_{t-1}$ represents the cumulated amount of funding received till year t from either VC firms or in the form of PLs, lagged by 1 year. The amounts are expressed in terms of logarithms of EUR received. Before matching, the median average injection of resources per company by VC is 200,000 EUR, while that of PLs is 150,000 EUR. Interestingly, a t-test shows that the two means are not significantly different at standard confidence levels (we obtain similar statistics in the matched sample).

Additionally, we are interested in studying which VC investors' characteristics drive their ability to add value to the target companies. We expect that VC firms with a sizable amount of funds under management, a broader experience and a manageable number of portfolio companies per investment manager are more likely to add value.

To test the impact of VC size (Hypothesis 2), we substitute VC_{t-1} with two dummy variables, $SmallVC_{t-1}$ and $LargeVC_{t-1}$, equal to 1 if the lead VC investor that invested in the target company had respectively less and more than 50 million EUR of capital under management.[7] Before the first investment, both variables are equal to 0 (therefore, $SmallVC_{t-1}$ + $LargeVC_{t-1}$ = VC_{t-1}).

We proceed in a similar way to test the impact of VC experience (Hypothesis 3). We substitute VC_{t-1} with the dummy variables $InexperiencedVC_{t-1}$ and $ExperiencedVC_{t-1}$. The former turns from 0 to 1 in the year of the first investment received by the focal company, if the investor was 'inexperienced'. The latter turns from 0 to 1 in the year of the first investment received by the focal company, if the investor was 'experienced'. We define as 'inexperienced' investors those falling in the first quartile of the number of investments carried out in the last 5 years (i.e., had reported less than 11 investments) in our sample, and as 'experienced' investors the remaining ones.

Lastly, to test Hypothesis 4 we consider the number of companies per investment manager for each VC investor, which indicates how much attention the VC firm can dedicate to each of its portfolio companies. We split VC_t into two dummy variables: $LowAttentionVC_{t-1}$ and $HighAttentionVC_{t-1}$. The former is equal to 1 for VC investors with a number of portfolio companies per VC manager in the last quartile (i.e., higher than 9.8), whereas the latter is equal to 1 for the remaining VC investors.

As we believe that VC firms with more capital under management, a broader experience and devoting a higher attention are better able to add value to the target companies, we expect

[7] We should mention that, due to confidentiality reasons, we do not have the complete information about the exact amount of capital managed by each VC firm per year. Rather, we rely on the classification of VC investors as small versus large provided by the Spanish Venture Capital Association (ASCRI), which is based on the range of capital under management. ASCRI classifies a VC investor as small if the capital under management is lower than 50 million EUR. Thus, we use this threshold applied by ASCRI to identify small versus large VC firms in Spain.

$LargeVC_{t-1}$, $ExperiencedVC_{t-1}$ and $HighAttentionVC_{t-1}$ to have positive coefficients, and significantly higher than that of PL_{t-1}.[8]

Tables 3 and 4 show the descriptive statistics of the main variables and the correlation matrix, respectively.

Table 3: Variable summary statistics

	N	Mean	Std. Dev.	Min	Max
$lnSales_t$	3,534	12.331	3.040	0.000	21.224
$lnEmployees_t$	3,471	2.006	1.224	0.000	8.418
$lnTotalAssets_t$	3,534	13.699	1.878	6.592	22.567
$lnCash_{t-1}$	3,534	10.898	2.623	0.000	19.681
$Intangibles_{t-1}$	3,534	0.176	0.245	0.000	1.000
Age_t	3,534	5.548	3.244	1.000	17.000
VC_{t-1}	3,534	0.261	0.439	0.000	1.000
PL_{t-1}	3,534	0.189	0.392	0.000	1.000
$lnAmount_{t-1}$	3,530	7.888	11.104	0.000	90.717
$SmallVC_{t-1}$ (1- $LargeVC_{t-1}$)	3,534	0.859	0.348	0.000	1.000
$InexperiencedVC_{t-1}$ (1- $ExperiencedVC_{t-1}$)	3,534	0.251	0.434	0.000	1.000
$LowAttentionVC_{t-1}$ (1- $HighAttentionVC_{t-1}$)	3,534	0.909	0.288	0.000	1.000

$lnSales_t$, $lnEmployees_t$, and $lnTotalAssets_t$ are equal to the logarithm of gross sales, the number of employees, and total assets of companies, plus 1, respectively. $lnCash_{t-1}$ is the logarithm of cash available plus 1, lagged by one year. $Intangibles_{t-1}$ is the percentage of intangible assets on total assets, lagged by one year. Age_t is measured in years. VC_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC, lagged by one year. PL_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives its first PL, lagged by one year. $lnAmount_{t-1}$ is the cumulated amount of either VC or PL funding received till year *t*, lagged by 1 year. $SmallVC_{t-1}$ is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor had less than 50 million EUR of capital under management, lagged by one year. $InexperiencedVC_{t-1}$ is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor falls in the first quartile in our sample in terms of number of investments carried out in the last 5 years, lagged by one year. $LowAttentionVC_{t-1}$ is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor has a number of portfolio companies per manager in the last quartile, lagged by one year.

[8] Please, note that all these variables $SmallVC_{t-1}$ and $LargeVC_{t-1}$; $InexperiencedVC_{t-1}$ and $ExperiencedVC_{t-1}$ and $LowAttentionVC_{t-1}$ and $HighAttentionVC_{t-1}$ are all step variables that turn from 0 to 1 in the year in which the company receives the first round of VC financing, lagged by one year. Depending on the characteristics of the first VC investor, one of the two variables in each pair will turn to 1 whereas the other will stay equal to 0.

Table 4: Variable correlation matrix

		1	2	3	4	5	6	7	8	9	10	11
1	$lnSales_t$	1.000										
2	$lnEmployees_t$	**0.628**	1.000									
3	$lnTotalAssets_t$	**0.395**	**0.622**	1.000								
4	$lnCash_{t-1}$	**0.289**	**0.440**	**0.600**	1.000							
5	$Intangibles_{t-1}$	**-0.077**	0.013	0.035	**-0.086**	1.000						
6	Age_t	**0.214**	**0.259**	**0.267**	**0.218**	**-0.097**	1.000					
7	VC_{t-1}	**0.172**	**0.270**	**0.306**	**0.202**	0.034	**0.190**	1.000				
8	PL_{t-1}	**0.095**	**0.151**	**0.151**	**0.141**	**0.166**	**0.098**	**-0.292**	1.000			
9	$lnAmount_{t-1}$	**0.209**	**0.354**	**0.401**	**0.295**	**0.183**	**0.309**	**0.567**	**0.356**	1.000		
10	$SmallVC_{t-1}$	**0.082**	**0.094**	**0.182**	**0.090**	**-0.043**	**0.056**	**0.420**	**-0.198**	**0.190**	1.000	
11	$InexperiencedVC_{t-1}$	**-0.077**	**-0.164**	**-0.191**	**-0.076**	**-0.074**	-0.032	**-0.739**	**0.283**	**-0.394**	**-0.258**	1.000
12	$LowAttentionVC_{t-1}$	**0.055**	**0.097**	0.038	0.027	0.009	**0.068**	**0.419**	**-0.155**	**0.191**	**0.161**	**-0.415**

The correlation matrix is based on 3,467 observations.

$lnSales_t$, $lnEmployees_t$, and $lnTotalAssets_t$ are equal to the logarithm of gross sales, the number of employees, and total assets of companies, plus 1, respectively. $lnCash_{t-1}$ is the logarithm of cash available plus 1, lagged by one year. $Intangibles_{t-1}$ is the percentage of intangible assets on total assets, lagged by one year. Age_t is measured in years. VC_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC, lagged by one year. PL_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives its first PL, lagged by one year. $lnAmount_{t-1}$ is the cumulated amount of either VC or PL funding received till year *t*, lagged by 1 year. $SmallVC_{t-1}$ is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor had less than 50 million EUR of capital under management, lagged by one year. $InexperiencedVC_{t-1}$ is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor falls in the first quartile in our sample in terms of the number of investments carried out in the last 5 years, lagged by one year. $LowAttentionVC_{t-1}$ is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor has a number of portfolio companies per manager in the last quartile, lagged by one year.
Bold values correspond to correlation indexes significant with p-value<1%.

4. Results

4.1 Venture capital value added

Table 5 shows the results of the analysis in which we test Hypothesis 1. In columns I, II and III, we estimate the impact of our independent variables and controls on the growth of companies' sales, employment, and total assets, respectively. The coefficient of PL_{t-1} (α) captures the DD estimator for the impact of PLs, and the coefficient of VC_{t-1} (β) captures the DD estimator for the impact of VC. The difference of the coefficients of VC_{t-1} and PL_{t-1} is our DDD estimator of the value added provided by VC. We test whether such difference is significant (H_0: $\alpha = \beta$), and report the Wald *F*-test significance in the last row of the table.

In each of the first three columns of Table 5, the coefficients of PL_{t-1} reveal that PLs have a positive effect on sales (p-value<10%), employment (p-value<1%) and total assets growth (p-value<1%). Similarly, VC_{t-1} has a positive and significant impact on all three growth dimensions (p-value<1%). These results indicate that both VC-backed firms and PL-backed firms have a higher growth than non-treated firms, after the receipt of the treatment, thus corroborating the existing evidence (Bertoni et al., 2017; Grilli and Murtinu, 2014). The magnitude of the effect of VC is bigger than that of PLs. The difference is significant for employment and total assets growth (p-value<5%), and close to significance for sales (p-value=0.111). The result suggests that VC improves the performance of target companies more than PLs, as hypothesized in our Hypothesis 1.

In columns IV, V and VI we replicate the analysis by controlling for the amount of financial resources injected. $lnAmount_{t-1}$ has positive and significant coefficients along the employment (p-value<5%) and total assets (p-value<10%) growth dimensions, suggesting that the injection of financial resources allows companies to hire more workers and to invest more in assets. Interestingly, the effect of PLs is notably less significant in these models with respect to the previous three (p-value<10%, and only for sales and employment growth). This result is coherent with the fact that PLs do not add value beyond the injection of financial resources. The effect of VC remains instead sizable and significant, and larger than that of PLs along the employment and the total assets dimensions. The magnitude of the effect is 15.7 percentage points (0.283-0.126) greater in employment growth (p-value<5%) and 14.8 percentage points (0.223-0.075) bigger for growth in total assets (p-value<10%). Again, for sales growth, the effect of VC is not significantly different from the one of PLs, although the test of difference of the coefficients is close to significance (p-value=0.108). These results support the idea that VC improves the performance of portfolio companies more than PLs, and we argue that the difference is explained by the value added by VC investors to portfolio companies in addition to the injection of financial resources, thus further corroborating our Hypothesis 1.

Table 5: Performance of VC-backed and PL-backed companies with respect to non-treated companies

	I		II		III		IV		V		VI	
Dep. Var.	$lnSales_t$		$lnEmployees_t$		$lnTotalAssets_t$		$lnSales_t$		$lnEmployees_t$		$lnTotalAssets_t$	
PL_{t-1} (α)	0.410	*	0.230	***	0.256	***	0.388	*	0.126	*	0.075	
	(0.220)		(0.054)		(0.066)		(0.234)		(0.065)		(0.070)	
VC_{t-1} (β)	0.869	***	0.400	***	0.431	***	0.848	***	0.283	***	0.223	***
	(0.258)		(0.065)		(0.072)		(0.249)		(0.071)		(0.072)	
$lnAmount_{t-1}$							0.002		0.009	**	0.015	***
							(0.009)		(0.003)		(0.003)	
$lnCash_{t-1}$	0.074	**	0.047	***	0.083	***	0.076	**	0.045	***	0.079	***
	(0.030)		(0.007)		(0.011)		(0.030)		(0.007)		(0.011)	
$Intangibles_{t-1}$	0.152		0.039		0.664	***	0.156		0.012		0.619	***
	(0.313)		(0.086)		(0.105)		(0.317)		(0.087)		(0.104)	
Age_t	0.053		0.044	***	0.087	***	0.035		0.034	**	0.072	***
	(0.058)		(0.014)		(0.020)		(0.058)		(0.015)		(0.021)	
Constant	10.541	***	0.931	***	11.842	***	10.547	***	0.991	***	11.938	***
	(0.483)		(0.124)		(0.164)		(0.490)		(0.127)		(0.165)	
N of observations	3534		3587		3651		3530		3583		3647	
N of companies	659		654		659		658		653		658	
F	6.341	***	25.693	***	40.693	***	5.778	***	24.189	***	39.627	***
R^2	0.052		0.16		0.259		0.053		0.166		0.27	
F, H0: $\alpha = \beta$	2.541		5.113	**	4.479	**	2.588		4.478	**	3.428	*

The sample includes VC-backed, PL-backed and non-treated companies. The table shows coefficients and, in parentheses, robust standard errors of fixed effects models whose dependent variables are specified in the first line of the table. $lnSales_t$, $lnEmployees_t$, and $lnTotalAssets_t$ are equal to the logarithm of gross sales, the number of employees, and total assets of companies, plus 1, respectively. VC_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC, lagged by one year. PL_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives its first PL, lagged by one year. $lnAmount_{t-1}$ is the cumulated amount of either VC or PL funding received till year *t*, lagged by 1 year. $lnCash_{t-1}$ is the logarithm of cash available plus 1, lagged by one year. $Intangibles_{t-1}$ is the percentage of intangible assets on total assets, lagged by one year. Age_t is measured in years. Time fixed effects are included.
* p-value<10%, ** p-value<5%, *** p-value<1%.

4.2 Drivers of VC value added

We now proceed to test our hypotheses related to the drivers of VC value added, i.e., VC size (Hypothesis 2), experience (Hypothesis 3) and attention to portfolio companies (Hypothesis 4). In the models reported in Table 6, we test the effect of VC size by splitting VC_{t-1} into $LargeVC_{t-1}$ and $SmallVC_{t-1}$. The results on the effect of PL_{t-1} (α) and control variables remain substantially unchanged in this model specification. We find that both small and large VC firms exert a positive effect on company's growth, with the exception of small VC firms (γ) in the case of employment growth. At the bottom of the table, we test whether the effect of PLs is the same as the one of large (α=β) and small (α=γ) VC firms. We find that VC firms with more capital under management show a stronger effect than PLs in the case of sales (p-value<10%) and employment (p-value<1%) growth, thus mostly supporting our Hypothesis 2. Conversely, we do not find significant differences when we compare the effect of Small VC firms with that of PLs in any of our three variables of interest, as the F test $\alpha = \gamma$ is never significant.

Table 7 shows the results of the analysis when we substitute VC_{t-1} with the variables $ExperiencedVC_{t-1}$ and $InexperiencedVC_{t-1}$. Again, we find that both variables have positive coefficients in all models but the former is more significant than the latter (p-value<1% for $ExperiencedVC_{t-1}$ in all models whereas $InexperiencedVC_{t-1}$ loses significance in the model of sales growth). We also find that the coefficient of $ExperiencedVC_{t-1}$ is significantly different from that of PL_{t-1} in all models (the test $\alpha = \beta$ has p-value<10%, at least), while the coefficient of $InexperiencedVC_{t-1}$ is not (the test $\alpha = \gamma$ is never significant), thus supporting our Hypothesis 3.

Lastly, in Table 8, we study the value of VC attention by substituting VC_{t-1} with $HighAttentionVC_{t-1}$ and $LowAttentionVC_{t-1}$. Both variables have positive and significant coefficients (p-value<5% at least, with the only exception of $LowAttentionVC_{t-1}$ in the model of total assets growth). We find that the effect is more significant for high attention VC firms (β) than for low attention VC firms (γ). However, only $HighAttentionVC_{t-1}$ has an effect which is significantly higher than that of PL_{t-1} (F test $\alpha = \beta$, p-value<10%, at least). The coefficient of $LowAttentionVC_{t-1}$, instead, is not significantly different than the one of PL_{t-1} (F test $\alpha = \gamma$). This provides support to our Hypothesis 4.

Table 6: Performance of VC-backed and PL-backed companies with respect to non-treated companies: the role of VC size

	I		II		III	
Dep. Var.	*$lnSales_t$*		*$lnEmployees_t$*		*$lnTotalAssets_t$*	
PL_{t-1} (α)	0.388	*	0.126	**	0.075	
	(0.234)		(0.063)		(0.070)	
$LargeVC_{t-1}$ (β)	0.973	***	0.405	***	0.189	**
	(0.311)		(0.087)		(0.084)	
$SmallVC_{t-1}$ (γ)	0.658	*	0.100		0.276	**
	(0.372)		(0.101)		(0.116)	
$lnAmount_{t-1}$	0.002		0.009	***	0.015	***
	(0.009)		(0.003)		(0.003)	
$lnCash_{t-1}$	0.075	**	0.045	***	0.079	***
	(0.030)		(0.007)		(0.011)	
$Intangibles_{t-1}$	0.145		0.002		0.622	***
	(0.316)		(0.087)		(0.104)	
Age_t	0.035		0.035	**	0.072	***
	(0.058)		(0.015)		(0.021)	
Constant	10.556	***	0.999	***	11.936	***
	(0.491)		(0.125)		(0.165)	
N of observations	3530		3583		3647	
N of companies	658		653		658	
F	5.341	***	23.497	***	36.77	***
R^2	0.054		0.172		0.271	
F, H0: $\alpha = \beta$	2.977	*	10.724	***	1.669	
F, H0: $\alpha = \gamma$	0.454		0.059		2.630	

The sample includes VC-backed, PL-backed and non-treated companies. The table shows coefficients and, in parentheses, robust standard errors of fixed effects models whose dependent variables are specified in the first line of the table. *$lnSales_t$*, *$lnEmployees_t$*, and *$lnTotalAssets_t$* are equal to the logarithm of gross sales, the number of employees, and total assets of companies, plus 1, respectively. *PL_{t-1}* is a dummy that turns from 0 to 1 in the year in which a company receives its first PL, lagged by one year. *$LargeVC_{t-1}$* is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor had more than 50 million EUR of capital under management, lagged by one year. *$SmallVC_{t-1}$* is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor had less than 50 million EUR of capital under management, lagged by one year. *$lnAmount_{t-1}$* is the cumulated amount of either VC or PL funding received till year *t*, lagged by 1 year. *$lnCash_{t-1}$* is the logarithm of cash available plus 1, lagged by one year. *$Intangibles_{t-1}$* is the percentage of intangible assets on total assets, lagged by one year. *Age_t* is measured in years. Time fixed effects are included.

* p-value<10%, ** p-value<5%, *** p-value<1%.

Table 7: Performance of VC-backed and PL-backed companies with respect to non-treated companies: the role of VC experience

	I		II		III	
Dep. Var.	$lnSales_t$		$lnEmployees_t$		$lnTotalAssets_t$	
PL_{t-1} (α)	0.405	*	0.131	**	0.074	
	(0.236)		(0.065)		(0.070)	
$ExperiencedVC_{t-1}$ (β)	0.944	***	0.314	***	0.219	***
	(0.263)		(0.074)		(0.073)	
$InexperiencedVC_{t-1}$ (γ)	0.579		0.198	*	0.236	**
	(0.397)		(0.112)		(0.098)	
$lnAmount_{t-1}$	0.000		0.008	**	0.015	***
	(0.010)		(0.003)		(0.003)	
$lnCash_{t-1}$	0.076	**	0.045	***	0.079	***
	(0.030)		(0.007)		(0.011)	
$Intangibles_{t-1}$	0.151		0.010		0.619	***
	(0.317)		(0.087)		(0.104)	
Age_t	0.038		0.035	**	0.072	***
	(0.059)		(0.015)		(0.021)	
Constant	10.536	***	0.987	***	11.938	***
	(0.491)		(0.126)		(0.165)	
N of observations	3530		3583		3647	
N of companies	658		653		658	
F	5.495	***	22.711	***	36.39	***
R^2	0.054		0.168		0.270	
F, H0: $\alpha = \beta$	3.529	*	5.958	**	3.206	*
F, H0: $\alpha = \gamma$	0.149		0.307		2.337	

The sample includes VC-backed, PL-backed and non-treated companies. The table shows coefficients and, in parentheses, robust standard errors of fixed effects models whose dependent variables are specified in the first line of the table. $lnSales_t$, $lnEmployees_t$, and $lnTotalAssets_t$ are equal to the logarithm of gross sales, the number of employees, and total assets of companies, plus 1, respectively. PL_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives its first PL, lagged by one year. $ExperiencedVC_{t-1}$ is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor does not fall in the first quartile in our sample in terms of number of investments carried out in the last 5 years, lagged by one year. $InexperiencedVC_{t-1}$ is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor falls in the first quartile in our sample in terms of the number of investments carried out in the last 5 years, lagged by one year. $lnAmount_{t-1}$ is the cumulated amount of either VC or PL funding received till year t, lagged by 1 year. $lnCash_{t-1}$ is the logarithm of cash available plus 1, lagged by one year. $Intangibles_{t-1}$ is the percentage of intangible assets on total assets, lagged by one year. Age_t is measured in years.
* p-value<10%, ** p-value<5%, *** p-value<1%.

Table 8: Performance of VC-backed and PL-backed companies with respect to non-treated companies: the role of VC attention

	I		II		III	
Dep. Var.	$lnSales_t$		$lnEmployees_t$		$lnTotalAssets_t$	
PL_{t-1} (α)	0.383		0.124	*	0.073	
	(0.234)		(0.065)		(0.071)	
$HighAttentionVC_{t-1}$ (β)	0.927	***	0.317	***	0.264	***
	(0.264)		(0.074)		(0.075)	
$LowAttentionVC_{t-1}$ (γ)	0.636	***	0.192	**	0.115	
	(0.242)		(0.084)		(0.078)	
$lnAmount_{t-1}$	0.002		0.009	**	0.015	***
	(0.009)		(0.003)		(0.003)	
$lnCash_{t-1}$	0.075	**	0.045	***	0.079	***
	(0.030)		(0.007)		(0.011)	
$Intangibles_{t-1}$	0.162		0.014		0.621	***
	(0.316)		(0.087)		(0.104)	
Age_t	0.036		0.035	**	0.072	***
	(0.058)		(0.015)		(0.021)	
Constant	10.542	***	0.989	***	11.935	***
	(0.490)		(0.127)		(0.165)	
N of observations	3530		3583		3647	
N of companies	658		653		658	
F	5.358	***	22.445	***	36.426	***
R^2	0.054		0.168		0.272	
F, H0: $\alpha = \beta$	3.242	*	6.309	**	5.408	**
F, H0: $\alpha = \gamma$	0.842		0.601		0.233	

The sample includes VC-backed, PL-backed and non-treated companies. The table shows coefficients and, in parentheses, robust standard errors of fixed effects models whose dependent variables are specified in the first line of the table. $lnSales_t$, $lnEmployees_t$, and $lnTotalAssets_t$ are equal to the logarithm of gross sales, the number of employees, and total assets of companies, plus 1, respectively. PL_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives its first PL, lagged by one year. $HighAttentionVC_{t-1}$ is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor does not have a number of portfolio companies per investment manager in the last quartile, lagged by one year. $LowAttentionVC_{t-1}$ is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC if the VC investor has a number of portfolio companies per investment manager in the last quartile, lagged by one year. $lnAmount_{t-1}$ is the cumulated amount of either VC or PL funding received till year *t*, lagged by 1 year. $lnCash_{t-1}$ is the logarithm of cash available plus 1, lagged by one year. $Intangibles_{t-1}$ is the percentage of intangible assets on total assets, lagged by one year. Age_t is measured in years. Time fixed effects are included.
* p-value<10%, ** p-value<5%, *** p-value<1%.

Summing up, we find that the 'extra value' brought about by VC is driven by VC firms with a larger amount of capital under management, a broader experience and a limited number of companies per portfolio manager. Instead, small, inexperienced and VC firms with too many companies to follow with respect to the number of portfolio managers do not add much value, and only have an effect on company performance which is similar to that of PLs.

4.3 Alternative matching algorithms

As robustness checks, we replicate our analyses using alternative matching algorithms. First, instead of one pooled matching, we perform a year by year matching for each treatment year (2005 to 2011) and then pool the selected matching samples together. Second, instead of a pure PSM, we perform a PSM after a Coersened Exact Matching (CEM). The CEM (Iacus et al., 2012) allows us to exclude non-treated companies that do not share the characteristics of treated companies simultaneously along a set of discrete variables, in our case, age, size (based on the number of employees), industries, regions and years. Third, as in our main analysis, we match treated with non-treated companies in the year before a company is funded for the first time, by either a VC investor or a PL, we automatically loose 196 VC-backed and 58 PL-backed companies that were funded at birth and for which matching variables in the year of the matching are not available. Therefore, we made a separate matching for companies funded at birth in the year of the funding rather than one year earlier, and then add them to the other matched companies.

Our results are robust to these alternative matching algorithms. For the main analysis, they are shown in Tables A1 and A2 of the Appendix.[9]

4.4 Endogeneity of VC and PLs

An important assumption of our empirical approach is that VC-backed, PL-backed and non-treated companies are comparable, and only differ for the type of treatment they receive.

[9] Robustness checks on the analysis of the drivers of VC value added are available from the authors upon request.

The matching approach that we use so far helps us in identifying companies that are comparable along some *observable* characteristics that are used as matching variables (specifically, age, size, liquidity, asset intangibility, industry, region and year).

However, the matching approach does not ensure that the selected companies are comparable along *unobservable* characteristics (Smith and Todd, 2005). Nevertheless, those characteristics, such as the quality of the founding team, or the market potential, are relevant because they may affect not only the performance of companies but also the likelihood of receiving the treatment. For instance, VC is provided after careful screening of companies' potential. If companies that are more promising are more likely to achieve higher growth and also receive VC, then our variable of interest VC_{t-1} is endogenous, and we may have overestimated its effect on companies' growth.[10] The same reasoning can be applied to PLs, which are also provided after careful screening. If the effects of both PLs and VC are overstated in the same way, their difference (the DDD estimator) may still be unbiased. However, VC and PLs are awarded by different entities (a specialized investor on the one side and a governmental body on the other), which may have different objectives and therefore different screening criteria. Hence, it is possible that the estimated coefficients of PLs and VC are biased in different ways, and then their difference would be biased too.

To overcome this issue, we adopt a two-step Heckman-type estimation structure and employ a switching regression with endogenous switching methodology to disentangle the impact of screening and monitoring on the performance of VC-backed firms (see Chemmanur et al., 2011, and Guerini and Quas, 2015, for applications in the VC context). This procedure is discussed in detail in Heckman (1979) and Maddala (1983) and is a generalized version of the

[10] The fixed effect specification that we have used actually takes care of time invariant unobservable company's characteristics. However, some unobservable characteristics may change over time and lead to endogeneity issues.

traditional Heckman model. This model accounts for the effect of unobservable characteristics of sample companies by using inverse Mills ratios (IMRs).[11]

We consider the whole population of VC-backed, PL-backed and non-treated companies described in the first four columns of Table 1. In a first step, we retain observations only in the year of the treatment for VC-backed and PL-backed companies, and all observations for non-treated companies.[12] We model the probability of each company to receive either VC or PLs using a bivariate probit model whose dependent variables are VC_t and PL_t. The bivariate probit model allows us to simultaneously analyze two events that are interrelated, such as the receipt of VC and PLs. As independent variables, we use $lnCash_{t-1}$, $Intangibles_{t-1}$, Age_t and $lnTotalAssets_{t-1}$, plus year, industry and region dummies. Additionally, we include dummies identifying companies operating in high-tech manufacturing (*HighTechManufacturing*) and knowledge-intensive services (*KnowledgeIntensiveService*), according to the Eurostat classification based on the NACE Rev. 2 codes (Eurostat, 2015). Lastly, the identification of the endogenous switching regression requires the inclusion of instruments (Maddala, 1983). Following Brander et al. (2015), we include two variables that capture exogenous variations in the likelihood that a company receives VC or PLs: $lnVCfundraisingRegion_t$ and $lnENISAinvestmentsRegion_t$. The former is equal to the logarithm of the amount of funds raised by VC investors in each Spanish region (Source: Webcapitalriesgo) and is included in the model for VC_t. The latter is the logarithm of the number of PLs awarded in each Spanish region (Source: ENISA and Invertec). It is included in the model for PL_t. The results of this first step of the endogenous switching regression are shown in Table 9.

[11] Because of the complexity of this approach, we use it only in our main analysis and not in the analysis of the drivers of VC value added.

[12] To be more precise, we excluded observations of non-treated companies that were older than 10 years, for consistency with VC-backed and PL-backed companies in our sample, which received a treatment when they were up to 10 years old.

The ρ parameter of the bivariate probit model is positive and significant, suggesting that there are unobservable factors that affect the probabilities of receiving both VC and PLs. Moreover, we find that all the variables included in the model have the same sign in both probit models, and are highly significant (p-value<1%, with the exception of *KnowledgeIntensiveService*, which in the model for PL_t is only significant with p-value<10%). This confirms that the receipt of VC and PLs are not random processes, and happen after a careful selection of companies. Lastly, both $lnVCfundraisingRegion_t$ and $lnENISAinvestmentsRegion_t$ positively affect the probabilities of receiving VC (p-value<5%) and PLs (p-value<10%), respectively.

Table 9: First step of the endogenous switching regression model: probability of obtaining PLs and VC

	I	
Dependent Variables	PL_t	VC_t
$lnCash_{t-1}$	0.051***	0.048***
	(0.012)	(0.009)
$Intangibles_{t-1}$	1.719***	2.023***
	(0.078)	(0.073)
Age_t	-0.179***	-0.160***
	(0.011)	(0.010)
$lnTotalAssets_{t-1}$	0.105***	0.126***
	(0.016)	(0.014)
HighTechManufacturing	0.711***	0.391***
	(0.128)	(0.145)
KnowledgeIntensiveService	0.300***	0.152*
	(0.098)	(0.084)
$lnVCfundraisingRegion_t$	0.016**	
	(0.007)	
$lnENISAinvestmentsRegion_t$		0.119*
		(0.062)
Constant	-3.870***	-5.867***
	(0.183)	(0.902)
Ath ρ constant	0.764***	
	(0.039)	
N of observations	57,272	
χ^2	2,561.838***	
Wald test of ρ=0, χ^2	390.057***	

The table shows coefficients and, in parentheses, robust standard errors of a bivariate probit model whose dependent variables are specified in the first line of the table. VC_t is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC. PL_t is a dummy that turns from 0 to 1 in the year in which a company receives its first PL. $lnCash_{t-1}$ is the logarithm of cash available plus 1, lagged by one year. $Intangibles_{t-1}$ is the percentage of intangible assets on total assets, lagged by one year. Age_t is measured in years. $lnTotalAssets_{t-1}$ is equal to the logarithm of total assets plus 1, lagged by one year. *HighTechManufacturing* is a dummy that takes the value 1 for companies operating in high-tech manufacturing, according to the Eurostat classification based on the NACE Rev. 2 codes. *KnowledgeIntensiveService* is a dummy that takes the value 1 for companies classified as knowledge-intensive services, according to the Eurostat classification based on the NACE Rev. 2 codes. $lnVCfundraisingRegion_t$ is equal to the logarithm of the amount of funds raised by VC investors in each Spanish region (source: Webcapitalriesgo). $lnENISAinvestmentsRegion_t$. is the logarithm of the number of PLs awarded in each Spanish region (source: ENISA and Invertec). The sample includes PL-backed and VC-backed companies in the year of the first investment and in addition all observations for non-treated companies. Year, industry and region fixed effects are included.

* p-value<10%, ** p-value<5%, *** p-value<1%.

We use the results of the bivariate probit model to compute two IMRs, one for each treatment variable, *IMR_VC* and *IMR_PL*. We follow Brown (2011) and Henning and Henningsen (2007) to compute IMRs after the bivariate probit models. We then insert these IMRs as regressors in a second stage, in which we model sales, employment and total assets growth. We use a cross-section specification in the year of the treatment for VC-backed and PL-backed companies, separately. Companies that received both VC and PLs are excluded from the estimation process. The dependent variables are $Sales3YearsGrowth_t$, $Employees3YearsGrowth_t$ and $TotalAssets3YearsGrowth_t$. $Sales3YearsGrowth_t$ is the difference between the logarithm of sales two years after the treatment and the logarithm of sales one year earlier. In other terms, it is the logarithmic growth in the three years around the treatment. $Employees3YearsGrowth_t$ and $TotalAssets3YearsGrowth_t$ are computed in similar ways based on the number of employees and the total assets. As independent variables, besides IMRs, we use once again $lnCash_{t-1}$, $Intangibles_{t-1}$, size ($lnSales_{t-1}$, $lnEmployees_{t-1}$ or $lnTotalAssets_{t-1}$, depending on the model) measured one year before the treatment, Age_t and the logarithm of the cumulated amount received in the form of either PL or VC during the three years around the treatment ($lnAmount3Years_t$). We also control for the *HighTechManufacturing* and *KnowledgeIntensiveServices* dummies and for year, industry and regions fixed effects. We resort to an OLS model in which we bootstrap standard errors. The results are shown in Table 10.

Table 10: Second step of the endogenous switching regression model: three years growth of PL-backed and VC-backed companies

Dep. Variable	*Sales3YearsGrowth$_t$*		*Employees3YearsGrowth$_t$*		*TotalAssets3YearsGrowth$_t$*	
	I	*II*	*III*	*IV*	*V*	*VI*
Sample	*PL-backed*	*VC-backed*	*PL-backed*	*VC-backed*	*PL-backed*	*VC-backed*
lnSales$_{t-1}$	-0.760 ***	-0.693 ***				
	(0.032)	(0.053)				
lnEmployees$_{t-1}$			-0.322 ***	-0.369 ***		
			(0.059)	(0.050)		
lnTotalAssets$_{t-1}$					-0.457 ***	-0.480 ***
					(0.067)	(0.175)
lnCash$_{t-1}$	0.018	(0.150)	0.020	(0.034)	0.046	0.016
	(0.083)	(0.096)	(0.029)	(0.031)	(0.033)	(0.082)
Intangibles$_{t-1}$	-4.219 ***	-5.994 ***	-0.772	-0.996 *	-0.667	0.043
	(1.226)	(2.169)	(0.553)	(0.533)	(0.838)	(2.691)
Age$_t$	0.194 *	0.413 **	-0.014	-0.002	0.017	-0.101
	(0.101)	(0.210)	(0.040)	(0.059)	(0.075)	(0.293)
lnAmount3Years$_t$	0.030 **	0.004	0.015 ***	0.013 ***	0.025 ***	0.022 ***
	(0.012)	(0.013)	(0.004)	(0.003)	(0.005)	(0.004)
HighTechManufacturing	-1.855	-1.610	-0.163	-0.319	0.289	-0.254
	(1.589)	(1.760)	(0.440)	(0.300)	(0.368)	(1.126)
KnowledgeIntensiveService	-0.155	-0.449	-0.025	0.291	0.043	0.401
	(0.383)	(0.759)	(0.220)	(0.234)	(0.178)	(0.555)
IMR_PL	-1.061		-0.224		-0.210	
	(0.707)		(0.286)		(0.529)	
IMR_VC		-3.270 **		-0.622 *		-0.132
		(1.279)		(0.347)		(1.880)
Constant	12.162 ***	19.009 ***	1.657	3.042 ***	6.513 ***	6.979
	(2.739)	(4.019)	(1.014)	(1.092)	(2.267)	(7.358)
N of observations	344	243	336	293	361	300
Chi²	11382 ***	.	583.766 ***	47455.49 ***	3548.9 ***	.
R²	0.747	0.711	0.361	0.483	0.52	0.681

The table shows coefficients and, in parentheses, bootstrapped standard errors of OLS models whose dependent variables are specified in the first line of the table. In columns I, III and V, the sample includes PL-backed companies in the year of the first PL. In columns II, IV and VI, the sample includes VC-backed companies in the year of the first investment. *Sales3YearsGrowth$_t$* is the difference between the logarithm of sales 2 years after the treatment and the logarithm of sales 1 year earlier. *Employees3YearsGrowth$_t$* is the difference between the logarithm of employees 2 years after the treatment and the logarithm of employees 1 year earlier. *TotalAssets3YearsGrowth$_t$* is the difference between the logarithm of total assets 2 years after the treatment and the logarithm of total assets 1 year earlier. *lnSales$_{t-1}$*, *lnEmployees$_{t-1}$* and *lnTotalAssets$_{t-1}$* are equal to the logarithm of gross sales, number of employees, and total assets of companies, plus 1, respectively, lagged by one year. *lnCash$_{t-1}$* is the logarithm of cash available plus 1, lagged by one year. *Intangibles$_{t-1}$* is the percentage of intangible assets on total assets, lagged by one year. *Age$_t$* is measured in years. *lnAmount3Years$_t$* is the cumulated amount of either VC or PL funding received during the three years around the treatment. *HighTechManufacturing* is a dummy that takes the value 1 for companies operating in high-tech manufacturing, according to the Eurostat classification based on the NACE Rev. 2 codes. *KnowledgeIntensiveService* is a dummy that takes the value 1 for companies classified as knowledge-intensive services, according to the Eurostat classification based on the NACE Rev. 2 codes. IMR stands for Inverse Mills Ratio. Year, industry and region fixed effects are included in all models.
* p-value<10%, ** p-value<5%, *** p-value<1%.

The size in the year before the treatment is a significant predictor of the growth rate in the three following years, as $lnSales_{t-1}$, $lnEmployees_{t-1}$ and $lnTotalAssets_{t-1}$ have all positive coefficients (p-value<1%). $lnAmount3Years_t$ has a positive effect on growth in all models (p-value<1%), with the only exception of sales growth for VC-backed companies. *IMR_PL* is not significant in the growth models, suggesting that unobservable variables that determine the probability of receiving PLs do not significantly affect companies' growth as well. On the contrary, *IMR_VC* is significant in the models related to sales and employment growth, confirming the endogeneity of the VC treatment. These models are used to predict the growth of VC-backed and PL-backed companies. The predicted growths are then used to conduct a 'what if' analysis. We estimate what would have happened to VC-backed companies if they had received PLs instead of VC by applying the coefficients of the model of growth for PL-backed companies to VC-backed companies. Vice-versa, we estimate the growth of PL-backed companies if they had received VC instead of PLs by applying coefficients of the VC-backed companies' growth to PL-backed companies. Finally, we compare the estimated 'what if' growth with the actual growth, as shown in Table 11.

The 'what if' analysis indicates that VC-backed companies would have grown 11.1% and 19.6% less in terms of employment and total assets, respectively, if they had received a PL rather than a VC investment (p-value<1%). These results are consistent with what we find in the main analysis and confirm, once again, that VC-backed companies grow more than PL-backed companies, ceteris paribus. The difference is arguably due to the value added of VC. We also find weak evidence on sales (similarly to what we find in the main analysis): PL-backed companies would have grown 23.2% more had they received VC instead of PLs (p-value<10%).

Table 11: 'What if' analysis: three years growth of control group, PL-backed and VC-backed companies

	Obs.	Mean	Std. Error	Difference	T-test
Sales3YearsGrowth$_t$					
PL-backed	344	1.953	3.714		
PL-backed if they were VC-backed	344	2.185	2.948	0.232	*
VC-backed	243	2.267	3.560		
VC-backed if they were PL-backed	243	2.259	3.342	-0.008	
Employees3YearsGrowth$_t$					
PL-backed	336	0.622	0.842		
PL-backed if they were VC-backed	336	0.689	0.657	0.068	
VC-backed	293	1.092	0.853		
VC-backed if they were PL-backed	293	0.981	0.518	-0.111	***
TotAssets3YearsGrowth$_t$					
PL-backed	361	1.169	1.167		
PL-backed if they were VC-backed	361	1.247	1.233	0.078	
VC-backed	300	1.855	1.336		
VC-backed if they were PL-backed	300	1.659	0.975	-0.196	***

The table shows statistics on the average sales, employment and total assets growth three years after treatment for CG, PL-backed and VC-backed companies, and compare it with the estimated growth if companies fell in the other categories. The 'what if' growth was predicted using the estimates shown in Table 10.
* p-value<10%, ** p-value<5%, *** p-value<1%.

5. Discussion and conclusions

The effect of VC on the performance of investee companies, which is widely accepted in the literature, is the result of three distinct effects: 1) the selection effect, due to the screening ability of VC managers, 2) the funding effect, due to the injection of financial resources and 3) the value-adding services provided to portfolio companies by VC managers. Most of the literature focuses on disentangling the effect of VC selection from that of value added, giving much less attention to funding effects. However, the importance of funding is not questioned since VC involvement implies an injection of money in financially constrained companies. Such injection can change completely the investment patterns of investees and unleash their potential, even in absence of a value added by the investor. By not appropriately considering the consequences of the funding effect of VC, we posit that extant literature may have overestimated the effect of value added on investee firms' performance.

In this work, we address this issue by comparing VC-backed firms with similar companies that receive external financing in the form of a hybrid instrument (namely, PL) from other institutions that did not provide value-adding services. We argue that by comparing VC-backed, PL-backed and control group companies we are able to isolate the impact of funding from the impact of value added on investee firms' performance, thus estimating the effects of VC value added more appropriately than previous studies. We take advantage of this setting to reveal the conditions under which VC are better able to add value to their portfolio companies.

Specifically, we resort to a difference-in-difference-in-difference (DDD) estimator. We use information on the Spanish populations of recently-established companies that received VC (830) or were granted a PL (929) between 2005 and 2011, and 14,111 untreated companies. We focus on growth as a common measure for ventures' performance. Even though all treated companies (i.e., VC-backed and PL-backed) grow more than untreated companies, we find VC-backed companies outperform PL-backed companies in employment, total assets and (less significantly) sales growth. Since both VC and PLs provide long-term equity (or quasi-equity) funding after a detailed screening process, we argue that the higher performance of VC-backed companies, when compared to their PL-backed peers, is explained by the value added that only VC firms provide. Regarding the magnitude of the effects, VC-backed companies grow more than PL-backed by 6.8 to 15.7 percentage points in terms of employment, and 7.8 to 14.8 percentage points in terms of total assets. Moreover, we find that the 'extra value' brought about by VC is driven by VC firms with more capital under management, with a broader experience and with a lower number of companies to oversee per VC manager. Our results are robust to alternative methodologies that control for the potential endogeneity of both VC and PLs.

As regards our main contribution, we extend the existing evidence on the overall positive effect of VC financing on investees' performance by presenting a novel approach to disentangle the impact of the value-adding services provided to VC-backed firms from the mere effect of long-term funding supplied to entrepreneurial companies, after a detailed screening process. Our results firmly endorse the value creation abilities of VC managers beyond the pure provision of long-term finance to selected companies. We also find that value added is not automatically provided by all VC firms. Only VC firms that are large enough, have enough experience and devote enough attention to their portfolio companies are able to provide not only money but also value added.

These results have important implications for VC investors. To achieve investment success, reaching a critical mass in terms of size and experience, and devoting enough attention to each portfolio company, are necessary strategies for ensuring the growth of the portfolio companies. Similarly, entrepreneurs shall consider the size, experience and number of investments by portfolio manager as important factors in selecting the most appropriate VC investor to approach. Policy makers may also find interesting implications in our results. We show that beneficiary firms receiving PLs from a government-backed institution grow more than untreated firms (although they grow less than VC-backed firms), thus providing support to the use of hybrid instruments. Extant literature did not find such positive effect for other forms of direct policy intervention, such as government-backed VC programs (e.g., Grilli and Murtinu, 2014). Our paper therefore supports the use of hybrid forms of governmental intervention to fund ventures. Moreover, it suggests that the negligible effect of governmental VC funds on their portfolio companies could be caused by their limited size, the lack of experience of their managers and/or a large number of portfolio companies compared to the number of investment managers.

Our study has some limitations that open the way to future research. First, our analysis is limited to the Spanish context. Spain presents a relatively well developed VC market (the fourth in terms of the amount invested) in Europe (Invest Europe, 2016) and is, therefore, an interesting test-bed for our hypothesis. However, a replication of the study on a larger and international database would ensure the generalizability of our results. Second, in addition to size, experience and attention, other factors may moderate the extent to which VC investors are able to add value to portfolio firms, such as the human capital available, the position in their social network or their affiliation (Bertoni et al., 2015; Nahata, 2008). While previous studies have shown that some of these factors improve VC-backed companies' performance, a replication of our approach would provide further proof that such effect is driven by the value added of VC. Third, it would be interesting to apply our approach to examine whether the value added by VC investors depends on the firm's idiosyncratic characteristics. For instance, it may have a stronger impact on companies that are more strongly affected by information asymmetries, such as younger and smaller companies, as well as those operating in high-technology industries.

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APPENDIX

Table A1: Performance of VC-backed and PL-backed companies with respect to non-treated companies: including companies funded at birth

	I		II		III	
Dep. Var.	*lnSales$_t$*		*lnEmployees$_t$*		*lnTotalAssets$_t$*	
PL_{t-1} (α)	0.420	*	0.128	**	0.093	
	(0.232)		(0.063)		(0.069)	
VC_{t-1} (β)	0.878	***	0.286	***	0.243	***
	(0.250)		(0.070)		(0.071)	
$lnAmount_{t-1}$	0.001		0.008	**	0.014	***
	(0.009)		(0.003)		(0.003)	
$lnCash_{t-1}$	0.067	**	0.045	***	0.073	***
	(0.027)		(0.007)		(0.010)	
$Intangibles_{t-1}$	0.042		0.032		0.608	***
	(0.309)		(0.084)		(0.108)	
Age_t	0.038		0.040	***	0.076	***
	(0.055)		(0.014)		(0.021)	
Constant	10.619	***	0.964	***	11.959	***
	(0.460)		(0.118)		(0.153)	
N of observations	3891		3969		4034	
N of companies	752		747		752	
F	5.822	***	24.901	***	39.395	***
R^2	0.050		0.159		0.242	
F, H0: $\alpha = \beta$	2.567		4.535	**	3.461	*

The table shows coefficients and, in parentheses, robust standard errors of FE models whose dependent variables are specified in the first line of the table. The sample includes VC-backed, PL-backed and non-treated companies. *lnSales$_t$*, *lnEmployees$_t$* and *lnTotalAssets$_t$* are equal to the logarithm of gross sales, number of employees, and total assets of companies, plus 1, respectively. VC_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC, lagged by one year. PL_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives its first PL, lagged by one year. $lnAmount_{t-1}$ is the cumulated amount of either VC or PL funding received till year *t*, lagged by 1 year. $lnCash_{t-1}$ is the logarithm of cash available plus 1, lagged by one year. $Intangibles_{t-1}$ is the percentage of intangible assets on total assets, lagged by one year. Age_t is measured in years. Time fixed effects are included.
* p-value<10%, ** p-value<5%, *** p-value<1%.

Table A2: Performance of VC-backed and PL-backed companies with respect to non-treated companies: different matching algorithms

Matching	Year by year PSM						CEM & PSM					
	I		II		III		IV		V		VI	
Dep. Var.	$lnSales_t$		$lnEmployees_t$		$lnTotalAssets_t$		$lnSales_t$		$lnEmployees_t$		$lnTotalAssets_t$	
PL_{t-1}	0.297		0.108		0.036		0.436		0.136		0.271	*
	(0.296)		(0.083)		(0.091)		(0.409)		(0.107)		(0.157)	
VC_{t-1}	0.850	***	0.210	**	0.199	**	0.747	**	0.195	**	0.221	**
	(0.309)		(0.086)		(0.092)		(0.291)		(0.079)		(0.089)	
$lnAmount_{t-1}$	(0.003)		0.007		0.012	***	0.008		0.012	**	0.016	***
	(0.011)		(0.004)		(0.005)		(0.012)		(0.004)		(0.005)	
$lnCash_{t-1}$	0.093	***	0.055	***	0.098	***	0.113	***	0.067	***	0.091	***
	(0.035)		(0.010)		(0.016)		(0.042)		(0.011)		(0.012)	
$Intangibles_{t-1}$	0.571		0.000		0.750	***	0.358		0.107		0.740	***
	(0.559)		(0.103)		(0.129)		(0.525)		(0.111)		(0.143)	
Age_t	0.140	**	0.041	**	0.091	***	0.096		0.015		0.082	***
	(0.062)		(0.018)		(0.024)		(0.070)		(0.017)		(0.025)	
Constant	10.758	***	1.009	***	11.887	***	10.236	***	0.632	***	11.400	***
	(0.578)		(0.163)		(0.215)		(0.589)		(0.161)		(0.163)	
N of observations	2510		2555		2588		1950		2015		2041	
N of companies	461		458		461		360		360		360	
F	4.72	***	13.758	***	28.647	***	3.764	***	12.563	***	23.509	***
R^2	0.054		0.161		0.3		0.053		0.182		0.325	
F, H0: $\alpha = \beta$	2.496		1.272		2.783	*	0.469		0.292		0.094	

The table shows coefficients and, in parentheses, robust standard errors of FE models whose dependent variables are specified in the first line of the table. The sample includes VC-backed, PL-backed and non-treated companies. The matching algorithm is a year by year PSM in columns I to III, and a combination of CEM and PSM in columns IV to VI. $lnSales_t$, $lnEmployees_t$ and $lnTotalAssets_t$ are equal to the logarithm of gross sales, number of employees, and total assets of companies, plus 1, respectively. VC_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives the first round of VC, lagged by one year. PL_{t-1} is a dummy that turns from 0 to 1 in the year in which a company receives its first PL, lagged by one year. $lnAmount_{t-1}$ is the cumulated amount of either VC or PL funding received till year *t*, lagged by 1 year. $lnCash_{t-1}$ is the logarithm of cash available plus 1, lagged by one year. $Intangibles_{t-1}$ is the percentage of intangible assets on total assets, lagged by one year. Age_t is measured in years. Time fixed effects are included. * p-value<10%, ** p-value<5%, *** p-value<1%.