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The European venture capital landscape: an EIF perspective

Volume V: The economic impact of VC investments supported by the EIF

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Abstract[†]

This paper examines the impact of venture capital (VC) investments supported by the EIF on the financial growth and performance of young and innovative firms. Using a novel dataset covering European start-ups supported by VC in the years 2007 to 2014, we generate a counterfactual group of non-VC-backed firms through a combination of exact and propensity score matching. To offset the relatively limited set of observables allowed by our data, we estimate treatment propensity using a series of innovative measures based on machine learning, network theory, and satellite imagery analysis. Our results document the positive effects of EIF-supported VC investments on start-up performance, as measured through various financial indicators (e.g. assets, revenue, employment). We find that VC financing enables start-ups to prioritise long-term growth, trading off short- to medium-term profitability if necessary. Overall, our work provides meaningful evidence towards the positive effects of EIF-supported VC investment on the financial growth of young and innovative businesses in Europe.

Keywords: EIF; venture capital; public intervention; real effects; start-ups; machine learning; geospatial analysis; network theory

JEL codes: G24, L25, M13, O38

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Non-technical Summary

This study constitutes the fifth volume of the working papers series entitled ”The European venture capital landscape: an EIF perspective”. The series aims at assessing how the EIF’s VC activity affected beneficiary start-up companies and contributes to the broader theme of government intervention in the field of venture capital (VC). This volume estimates the causal effects of VC investments supported by the EIF on the performance of start-ups. Accordingly, this work compares the financial growth of 782 early stage companies supported by the EIF in the years 2007 to 2014 — the treatment group — against a control group of non-VC-backed start-ups. Control start-ups are intended to mimic the growth trajectory of treated firms had they not received the VC investment.

Constructing an appropriate control group for VC-backed firms entails several challenges. To address these, we first map the entire set of European VC-invested start-ups in the years 2007 to 2014. This exercise is made possible by our partnership with Invest Europe, the association representing Europe’s Venture Capital and Private Equity industry. Invest Europe’s data, sourced directly from affiliated VC firms, provides an unrivalled coverage of the European VC ecosystem. We further rely on Bureau Van Dijk’s Orbis database to retrieve financial data. By combining Invest Europe and Orbis data, we create a novel dataset tracking all European start-ups backed by VC in 2007–2014.

We estimate the causal effects of VC investments, supported by the EIF, using Rubin’s Causal Model (Rubin, 1974), a standard tool in the econometric literature. A central assumption of Rubin’s framework is the correct identification of the assignment mechanism, i.e. the process that determines VC financing. To this end, we carry out an extensive review of the literature to build a comprehensive model of VC contracting. However, given that our dataset does not cater for the specific needs of the VC industry, we are constrained in the choice of drivers of VC financing that we can actually observe.

Against this background, we bring our model to the data by introducing various measures, some original to the VC literature. To predict the degree of innovation of start-ups, we use a machine learning algorithm trained to recognise highly innovative business models from short trade descriptions provided by the Orbis database. To measure the “accessibility” of start-ups vis-à-vis active VC firms, we use network theory, modelling the European VC ecosystem as a network of VC “hubs” connected by flight routes. Finally, to predict the start-up’s access to financing other than VC, we construct a proxy for the value of home equity based on satellite imagery analysis. This measure is based on the intuition that if housing supply in a given area is inelastic due to geographical constraints, demand shocks will directly translate into price shocks, rendering home equity a poor form of collateral to pledge against e.g., bank loans. We combine these innovative metrics with multiple other predictors of VC financing to construct our estimator, based on exact and propensity score matching.

Our results confirm the positive effects of EIF-supported VC investments on start-up growth, as measured through numerous financial indicators. In the first five years following the EIF-backed VC investment, treated start-ups tend to be one to two times more capitalised than their counterfactuals, with the spread between the two groups widening over time. EIF-backed start-ups also grow about two times larger than the control group in terms of assets. While in the first two years after investment this difference roughly equates to the amount of VC investment received, in subsequent periods the discrepancy extends above and beyond the amount of investment itself, pointing to the significant additionality of VC investments backed by the EIF.

The increase in funding brought by VC financing further propagates through the start-up's production function, positively affecting turnover levels for the treated. VC-backed start-ups achieve revenue levels ranging from 19 % to 97 % higher than the control group — one year and five years after treatment, respectively. Furthermore, treated firms benefit from increased employment levels — about 100% higher than control start-ups, as measured through cost of labour. This indicates that VC financing supported by the EIF spurs employment growth in start-ups.

Our results shed light on the accounting mechanism through which VC financing stimulates start-up growth. The VC investment generates a temporary imbalance that tends to favour equity over liabilities. This translates into excess liquidity that start-ups use to fuel their scaling up process. In the medium run, both the equity and cash surpluses are offset by an increased use of debt-type financing. VC-backed start-ups borrow significantly more than their counterfactuals, mostly to sustain their faster size growth. Given that this result is achieved through relatively lower shares of collateral (e.g. tangible assets) in their balance sheet, we can conclude that VC helps start-ups secure further debt financing.

VC-backed start-ups appear to trade off short-to-medium term profitability against achieving the desired scale of operations. While short-to-medium term financial losses are the norm for young and highly innovative start-ups, we find that VC-backed start-ups are less likely to report positive short-term profits compared to control firms. However, treated start-ups appear to catch-up with control firms in the medium term. In addition, we find no evidence of obvious cost inefficiencies brought by the VC financing itself. VC investments merely enable treated firms to trade off higher levels of short-term profitability than they could have otherwise had, in exchange of faster growth.

We do not detect significant deviations in the effects that can be attributed to start-up characteristics, with the exception of the geographic macro-region, e.g. UK and Ireland, France and Benelux exhibit higher growth. However, we argue that effects across macro-regions may not be entirely comparable, due to the large heterogeneity in the European VC ecosystem in terms of size and development of regional VC markets. We also carry out a battery of tests showing how our main results are maintained when accounting for various possible model specification errors. Moreover, our results are robust to potential missing data bias, caused by our data-intensive approach to causal inference.

To summarise our key results, we observe faster growth (in terms of assets) of start-ups supported by the EIF compared to non-VC-backed firms. This leads to higher capitalisation levels, higher revenues and higher job creation in the first five years following the VC investment. Moreover, we find higher investment and borrowing levels. These findings, in line with current economic research, point to the effectiveness of EIF's policy instruments fostering SME access to VC financing.

Overall, our work contributes to the development of an "impact culture" by estimating the causal effects of VC financing supported by the EIF. Our results provide meaningful evidence towards the impact of EIF VC on the financial growth of young and innovative businesses in Europe. Future work under this series, based on a similar approach, will tackle the impact of EIF-backed VC on investment outcomes and innovation.

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1 Introduction

Economists and policy makers widely acknowledge the role of young and innovative companies as net contributors to employment, innovation and productivity growth. This results not only from their individual importance in the economy, but also due to spillovers: the value created by start-ups' innovative activities often extends above and beyond single businesses, positively influencing other domestic firms and eventually the overall economy (Bertoni *et al.*, 2011).

Given that technological changes are crucial drivers of an evolving economy, governments have a vested interest in supporting start-ups and promoting their success. Moreover, information asymmetries and agency problems can lead to market failures affecting new ventures' access to traditional financing channels, motivating public intervention (Kraemer-Eis *et al.*, 2016; Colombo *et al.*, 2014).

In this respect, venture capital (VC) is an essential source of financing, able to support start-ups' drive towards growth and value creation. VC firms play a crucial role in mitigating information asymmetries, due to their ability to screen, monitor and mentor new entrepreneurial ideas. However, the venture capital ecosystem in Europe still experiences high fragmentation across (and within) national borders, as well as systematic issues like, inter alia, the risk of double taxation. Despite the recent positive developments, a fully unified European VC market remains an important long-term policy objective.

The EIF, through its VC activity, fulfils its public policy mission to support the formation of a resilient European VC ecosystem and the emergence of new European VC hubs. Together with own funds, EIF invests resources managed on behalf of capital providers/mandators under a range of programmes; it also advises and manages funds-of-funds and initiatives for third party investors. This has led to the EIF achieving a prominent role in the European VC ecosystem over the last twenty years. Kraemer-Eis *et al.* (2016) argue how this calls for a thorough assessment of EIF VC activities, to verify whether the initial policy goals were met. To this end, our work contributes to the series of EIF working papers "The European venture capital landscape: an EIF perspective", which tackles this important question.

The goal of this study is to compare the financial growth of start-ups supported by the EIF — the treatment group — against a control group of non-VC-backed start-ups. Our results confirm the positive effects of EIF-supported VC investments on start-up performance, as measured through various financial indicators (e.g. assets, revenue, employment). VC financing enables start-ups to prioritise long-term growth, trading off short- to medium-term profitability if necessary. Under the assumption that control start-ups correctly approximate the growth trajectory of treated firms had they not received the VC investment, our findings point to the positive causal effect of the EIF VC activity.

The paper is organised as follows: section 2 sets the scene by providing a brief literature review. Section 3 presents our main data sources, while section 4 discusses our econometric approach. Section 5 outlines our results and section 6 discusses their robustness. Section 7 concludes.

2 Literature review

A large body of literature documents the impact VC investments have on business growth, innovation and overall start-up success. These positive effects stem from two main channels. On the one hand, VC firms (VCs) can thoroughly evaluate innovative business ideas, which allows them to overcome some of the market imperfections that hinder young enterprises' access to finance (Colombo and Grilli, 2007). VCs alleviate information asymmetries and agency problems through their rigorous selection process, typically too costly for other financing institutions. A VC investment may additionally reduce uncertainty and transaction costs to the benefit of start-ups (Bottazzi and Da Rin, 2002; Davila *et al.*, 2003). On the other hand, VC firms can provide investees with supplementary value-adding services, further promoting their development (Busenitz *et al.*, 2004; Luukkonen *et al.*, 2013; Hellmann and Puri, 2000). For instance, VCs are known to provide vital managerial, financial, marketing and administrative advice (Croce *et al.*, 2013) and can introduce start-ups to their own network of business contacts (Cumming *et al.*, 2013; Hsu, 2006; Luukkonen *et al.*, 2013).

The importance of start-ups for the development of (pan-)national and regional economies, coupled with the desire to address potential supply-side weaknesses in domestic VC markets, is the primary reason for the creation of governmental VC funds (Bertoni and Tykvová, 2015; Colombo *et al.*, 2014; Lerner, 1999). Public policies to support VC can be broadly categorised in two types — direct and indirect public involvement (Cumming, 2014; Benoît and Surlemont, 2003). Indirect public intervention involves legislative instruments such as taxation policies, intellectual property rights, bankruptcy laws or contract laws to protect investors, shareholders and directors. Direct public involvement can take different forms depending on the way funds are disbursed (Colombo *et al.*, 2014). Governments can invest directly in start-ups through VC-like initiatives (*e.g.* business development banks). Moreover, they can co-invest with private VCs in hybrid-public funds. Lastly, public institutions may set up fund-of-funds, such as the EIF, acting as limited partners providing capital to VC funds.

There is still a lack of consensus in the economic literature about the effects of public intervention in the VC ecosystem. Studies focusing on North America tend to find that public intervention crowds-out the private VC market, that is, replacing rather than boosting private VC funding (Cumming and Macintosh, 2006; Brander *et al.*, 2008; Armour, 2006). However, research focussing on the European VC market has led to predominantly positive results. Brander *et al.* (2010), Guerini and Quas (2016) and Kraemer-Eis *et al.* (2016) study the effects of combined private and public VC support and find evidence of a crowding-in effect across a number of European markets. In this respect, Cumming (2014) emphasises the signalling effect of government VC, considered a "quality stamp" by most other private investors — see also Kraemer-Eis *et al.* (2018) for the case of the EIF.

A second strand of the literature has looked into the causal effects of VC investments on several dimensions of firm performance and across different geographies. Studies consistently identify positive results. In Davila *et al.* (2003) and Engel and Keilbach (2007), VC-backed start-ups were found to grow faster compared to non-VC-backed companies in terms of staff count in, respectively, US and Germany. Peneder (2010) finds comparable effects for Austrian firms and attributes these results to the monitoring activities of VCs and their ability to select companies displaying particularly high growth potential. Similarly, Chemmanur *et al.* (2011) associates VC-invested start-ups' higher productivity growth to VCs' screening and monitoring and find that it primarily stems from improvement in product market performance. Puri and Zarutskie (2012) also confirm North American VC-financed firms are on average larger and grow faster, in terms of both employment and sales. Finally, examining the Spanish VC market, Alemany and Martí (2005) find positive effects of VC on firm growth with respect to a series of outcomes — employment, assets, intangibles, and revenues.

Studies take advantage of different econometric techniques to draw conclusions on the effects of VC. Matching is the most common approach used to identify a counterfactual group (Puri and Zarutskie, 2012; Bottazzi and Da Rin, 2002; Hsu, 2006; Peneder, 2010; Alemany and Martí, 2005; Engel and Keilbach, 2007). The variables used in the matching process vary in the literature, but in general authors always include the firms' location, sector and age and further complement them with other available observable characteristics depending on the data source used. The treatment effects are then estimated with standard regressions on firm-level panel data. In addition to a matching approach, Chemmanur *et al.* (2011) employ a switching regression model to determine the firm productivity surplus that is attributable to VC. Da Rin *et al.* (2013) provide an extensive review of data sources and methods employed in the study of different aspects of the venture capital ecosystem.

The aggregate, macroeconomic effect of VC investments is a relatively under-explored topic in the literature. Nevertheless, existing studies also point to the positive macroeconomic effects of VC investments. Samila and Sorenson (2011) find that the increased local supply of VC encouraged entry, employment growth and aggregate income in the US economy. The authors' results stretch beyond the number of firms directly funded, due to VC-backed companies transferring knowledge onto their employees, which in turn motivates them to undertake further entrepreneurial endeavours. Popov and Roosenboom (2013) further confirm VC's positive effect on the creation of new businesses for 21 European countries. This diverse and extensive research validates venture capital's potential as an effective tool to encourage and support young companies. Hence, it highlights the importance of VC as a public policy instrument to promote growth and innovation across regions and sectors.

3 Data and methods

In this study, we exploit EIF's prominent role in the European VC ecosystem to evaluate the effects of venture capital investments on young and innovative start-ups. It is reasonable to assume that in the absence of EIF-backed VC investments, beneficiary start-ups would still pursue their entrepreneurial objectives by resorting, however, to alternative financing channels. This motivates our main econometric approach: in essence, we wish to compare start-ups supported by the EIF against non-VC-backed firms — treatment and control group respectively. A carefully designed control group will allow us to isolate the direct effects of VC investments on the financial growth of start-ups.

Constructing an appropriate control group entails several challenges. Nevertheless, the first requirement is straightforward: since the targeted control group is composed of non-VC-backed start-ups, we must ensure it does not include any VC-invested firm. To this end, we partnered with Invest Europe in the attempt to map the entirety of the European VC ecosystem. Invest Europe is the association representing Europe's Venture Capital and Private Equity industry.

To the best of our knowledge, Invest Europe's data provides an unrivalled coverage of the European VC ecosystem, also given that information is sourced directly from affiliated VC firms. However, since most other studies focus on country-level analyses (exploiting e.g, information from national registers), it is generally hard to draw meaningful comparisons. Brander *et al.* (2010) use the private database Thomson One to analyse 4,384 VC-invested EU start-ups between 2000 and 2008. Bottazzi and Da Rin (2002) identify 567 VC-backed firms listed on Euro.nm[1] between 1996 to 2000. Against this

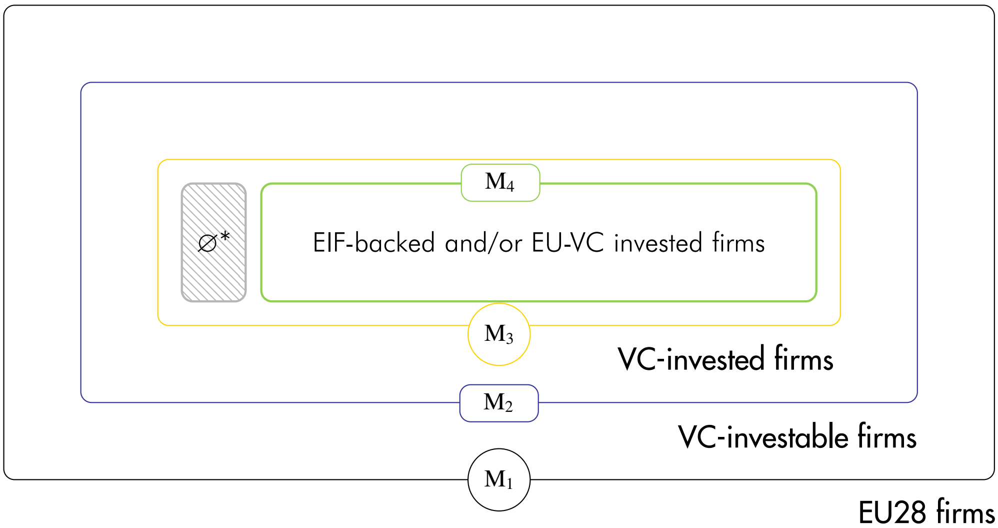
[1] The alliance of Europe's stock markets for innovative companies.

backdrop, our harmonised data on more than 11,500 start-ups supported by VC between 2007 and 2014 likely possesses the highest coverage of the European VC landscape to date.

The second important source of data concerns performance measures. Our main source of financial and industry activity data is Bureau Van Dijk's Orbis database. Orbis is an aggregator of firm-level data gathered from over 75 national and international information providers. Data is sourced from national banks, credit bureaus, business registers, statistical offices and company annual reports. There are several advantages in using the Orbis database over similar data sources (Kalemli-Ozcan *et al.*, 2015). Orbis provides harmonised balance sheet and profit and loss data, covering many more small and private companies compared to e.g. Compustat.[2] Furthermore, its detailed industry classification (e.g. 4-digit NACE codes) significantly enhances the characterisation of firms.

The remainder of this study relies on two important assumptions about the data presented so far. First, we need to assume that the Orbis database represents a random sample of the population of firms in the EU28, i.e. every EU28 company has the same probability of being included in Orbis. Second, we trust that the Invest Europe dataset is a complete representation of the population of VC-backed firms in Europe. Based on the two assumptions above, the combination of Invest Europe and Orbis data allows to isolate VC-backed start-ups from non-VC-backed firms. Moreover, it provides the foundation upon which we can build our strategy to identify the causal effect of VC investments supported by the EIF. Figure 1 illustrates our conceptual framework using a series of nested sets.[3] Figure 1 also introduces the set M_2, i.e. our control group. Its construction is addressed in section 4.

Figure 1: Identification of treatment and control populations



* The empty set ∅ reflects our assumption of data completeness for the VC population data.

In the following, we briefly discuss the plausibility of our assumptions. On the one hand, the Orbis database mimics the official firm size distribution (e.g. from Eurostat) for most European countries.

2 As of April 2019, Orbis tracks 300 million companies in over 90 countries. Only 1% of these are listed.

3 Formally, given sets $M_4 \subseteq M_3 \subset M_2 \subset M_1$ in Figure 1, our data assumptions are:

$$\Pr\{j \in O | j \in M_1\} = \rho \tag{1}$$

$$\Pr\{j \in M_3 | j \notin M_4, j \in O\} \approx 0 \tag{2}$$

where j is a given firm and O (not shown in Figure 1) is the set of companies that can be found in Orbis.

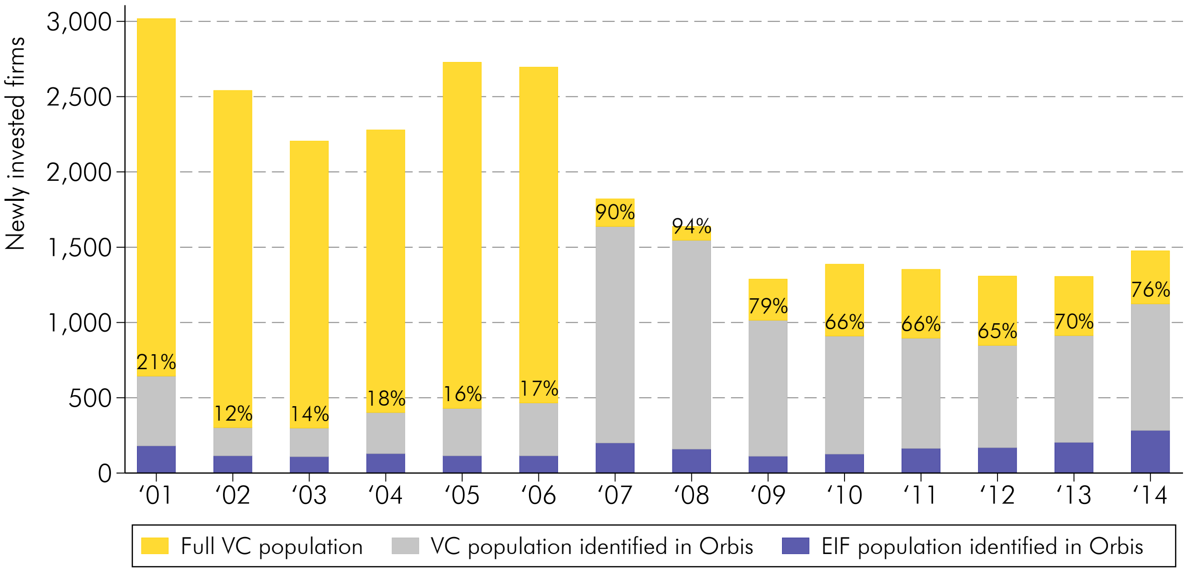
This indicates that the database likely satisfies our requirements. On the other hand, Orbis is a generalist database, not catering for the specific needs of the VC industry. This poses various challenges to the selection of counterfactuals, forcing us to make ample use of proxies and other indirect metrics.

To evaluate the completeness of our data on VC-backed start-ups, we combine Invest Europe's directory of VC-financed companies with EIF's own dataset, making sure the two sources overlap in terms of classifications and definitions. VC-backed companies are further identified in the Orbis database following a rigorous entity-matching methodology, controlling for name, location, sector, date of incorporation and/or fiscal ID. Figure 2 presents the entire population of VC-invested firms in Europe, since 2001 and by year of first investment. Figure 2 also portrays the share of start-ups identified in Orbis (grey), as well as the sample of EIF-supported start-ups identified in Orbis (blue).

Figure 2 shows that our dataset's coverage is considerably poorer before 2007. Only 16% of VC-backed start-ups are available to our analysis prior to 2007. However, following the implementation of a comprehensive data collection process, Invest Europe is since able to track in the Orbis database up to 80% of the entire population of VC-investees. The unobserved residual can almost exclusively be attributed to deficiencies in Orbis, which typically lacks company profiles for the remaining subset. For this reason, we focus on the economic effects of VC-backed companies invested in the period 2007 to 2014, where our claim of data completeness is very likely to hold.

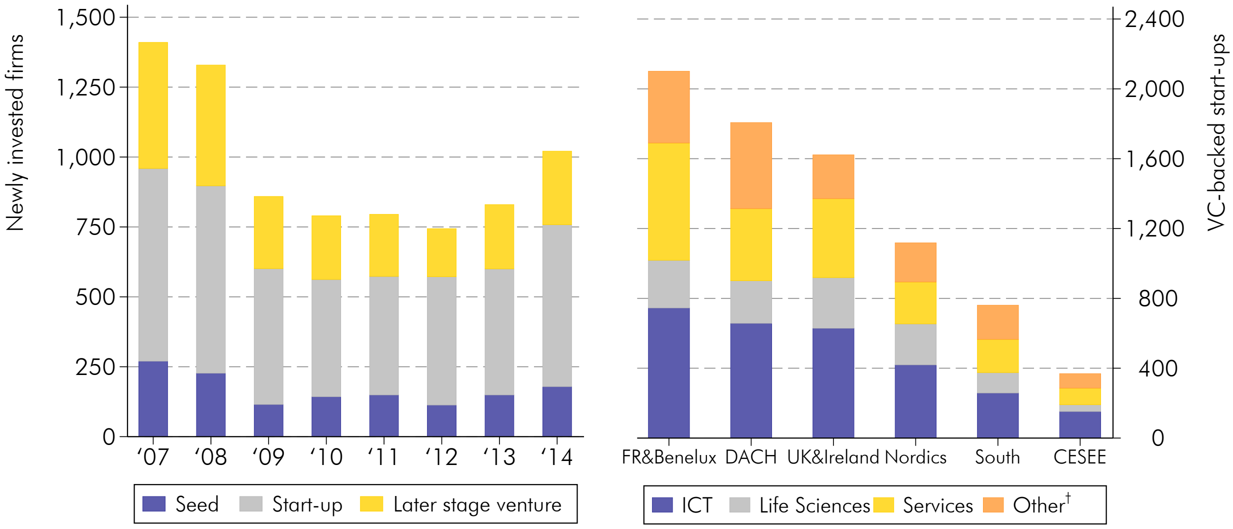
Figure 3 zooms into the distribution of the 8,943 European firms supported by VC in 2007-2014 and identified in the Orbis database. Figure 3a breaks down start-ups by their development stage when receiving VC investments. VC financing can be broadly classified into seed, start-up and later stage venture. Seed funding is generally provided to support product research, design, market testing and proof of concepts. Start-up financing is typically targeted at firms that have a fully developed product or service, so as to start mass production/distribution. As opposed to later-stage venture investments, seed and start-up investments reach firms that are usually pre-revenue.

Figure 2: Population of European VC-backed firms, by year of first investment



Note: The "full" population of VC-backed European start-ups is estimated from Invest Europe time series and the assumption that both domestic-to-foreign and initial-to-follow-on ratios, only available for the entire private equity segment, are also representative of the VC industry (i.e. seed, start-up, later stage venture). For aggregates prior to 2007, we further assume that foreign investments were distributed proportionally to the (domestic) market size of the target country.

Figure 3: Population of European VC-backed firms[6]



†Agriculture & environment; Chemical materials; Consumer goods & Business products; Construction & transport.

(a) By year of first investment and stage

(b) By geographic area and sector

Following Jeng and Wells (2000), we group firms in the seed and start-up stages under the collective term "early stage". Jeng and Wells recommend separating between early stage and later stage VC financing, both for purposes of analysis and policy implications. We adhere to their view and, for the scope of this study, we focus exclusively on early stage investments.[4]

Figure 3b illustrates the invested companies' distribution by sector and region. The regional classification follows Kraemer-Eis *et al.* (2016) and aggregates investees into six macro-regions.[5] We adapt Invest Europe's classification to identify and aggregate sectors (see Appendix A for details). Expectedly, Figure 3b shows that the largest share of firms across regions operate in the information and communication technology (ICT) sector, historically driving the ebbs and flows of the VC industry.

We further refine our initial treatment group by imposing a few more restrictions to our set of VC-backed firms. These are based on the empirical regularities characterising early stage start-ups, and are sought to create a homogeneous set of firms that will facilitate our analysis and address potential stage misclassification. These restrictions, first discussed in Kraemer-Eis *et al.* (2016), are detailed in Appendix B. Finally, in this paper we focus exclusively on start-ups supported by the EIF, which narrows down our initial treatment group to 782 VC-backed firms. These form the basis for the creation of our counterfactual group. Table 1 summarises the process leading to our final set of treated firms.

4 Empirical approach

This section details our empirical strategy towards the causal inference of VC investments' effects. Henceforth, VC-invested start-ups supported by the EIF in the period 2007-2014 will be referred to

4 We leave it to a future study to assess the economic impact of later stage VC financing backed by the EIF.

5 **DACH**: AT, DE; **NORDICS**: DK, FI, SE; **FR&BENELUX**: BE, FR, LU, NL; **SOUTH**: ES, GR, IT, MT, PT; **BI (British Isles)**: IE, UK; **CESEE**: BG, CY, CZ, EE, HR, HU, LT, LV, PL, RO, SI, SK.

6 Unless otherwise stated, all figures in this work are from the authors, based on EIF and Invest Europe data.

Table 1: VC-invested Firms Breakdown

Sample	Investees
Full European VC-backed population	27,044
- of which invested in 2007-2014	11,577
- of which identified in Orbis	8,943
- of which early stage	6,695
- of which early stage (stricter criteria)	4,945
- of which EIF	782

as the treatment group, while non-VC-backed firms will be called counterfactuals or controls. We first introduce and outline Rubin's Causal Model (Rubin, 1974). We then turn to a stylised representation of the VC financing process. We conclude by detailing our matching model, based on a combination of exact- and propensity score-based matching.

4.1 Identification strategy

Let Y_j be an outcome of interest for start-up j, with $j = 1 \ldots J$. Given a treatment W_j, each firm faces two potential outcomes: $Y_j(1)$ if it receives treatment, and $Y_j(0)$ in case it does not:

$$Y_j\left(W_j\right) = Y_j(0) \cdot \left(1 - W_j\right) + Y_j(1) \cdot W_j = \begin{cases} Y_j(0) & \text{if} \quad W_j = 0 \\ Y_j(1) & \text{if} \quad W_j = 1 \end{cases}$$

Against this backdrop, a measure of causal effect we are interested in is the average treatment effect on the treated (ATT), i.e. the average difference between the potential outcomes of treated firms:

$$\tau^t = \mathbb{E}\left(Y_j(1) - Y_j(0) \,\middle|\, W_j = 1\right)$$

The measure τ^t subtracts the outcome of treated start-up j from what would have otherwise happened had the VC investment not materialised. However, since only one of the two potential outcomes will ultimately take place, $Y(1)$ and $Y(0)$ cannot be simultaneously observed for the same start-up j. This leads to the inability to identify the measure τ^t. Rubin's Causal Model (Rubin, 1974, hereafter RCM) provides a solution for the identification problem by means of a formal mathematical framework.

RCM rests on three key assumptions, worth summarising here. The first — the stable unit treatment value assumption — states that the potential outcome of firm j must not be affected by the treatment status of other firms (Rubin, 1978). In other words, the success (or failure, for that matter) of any VC-invested start-up must not affect the outcome of other companies, and vice-versa. While this assumption could in principle be violated in the case of e.g., financial contagion, industrial linkages, Figure 3b showed that VC-backed firms are rather well diversified in terms of geography and industry, and constitute a very small portion of all businesses. Thus, meaningful financial spillovers are unlikely.

The second assumption is named conditional independence, or unconfoundedness.[7] Intuitively, if the process leading to VC financing were to be almost entirely caused by some measurable attributes of start-ups, then econometricians could look at firms with high predicted likelihood of treatment, yet no treatment status: these would represent appropriate counterfactuals because of their unexplained,

[7] It is also called selection-on-observables, since covariates contributing to treatment assignment are held fixed and are assumed to be known to the econometrician (Rosenbaum and Rubin, 1983).

"random" exclusion from the treatment group.[8] Thus, this assumption provides justification for the causal interpretation of estimated effects. To satisfy this important assumption, in section 4.2 we present a stylised model for the assignment mechanism, i.e. the process that determines VC financing.

Finally, RCM assumes overlap, i.e. that the treatment is not completely determined by any single or set of characteristics $\mathbf{X}_j$. Thus, there must be some overlap between treated and control firms in terms of treatment propensity. Using counterfactual firms whose likelihood of being treated lies in the treatment firms' probability range — the so-called common support condition — ensures this assumption holds. The combination of unconfoundedness and overlap is referred to as *strong ignorability* (Rosenbaum and Rubin, 1983). Formally, the two can be written as:

$$W_j \perp\!\!\!\perp \left(Y_j(0), Y_j(1)\right) \,\middle|\, \mathbf{X}_j \tag{3}$$

$$0 < \Pr\left(W_j \,\middle|\, \mathbf{X}_j = \mathbf{x}\right) < 1, \quad \forall \mathbf{x} \tag{4}$$

Under assumptions 3 and 4, we can replace the unobserved potential outcome $Y_j(0) \,|\, W_j = 1$ with $Y_j(0) \,|\, W_j = 0$, i.e. the observed outcome of appropriate control firms, to consistently estimate τ^t.

4.2 The treatment assignment mechanism

In this section, we provide a formal model for the treatment assignment mechanism of VC financing. As stated above, the assignment mechanism determines the exposure of start-ups to the treatment, i.e. the VC investment. To this end, we carry out an extensive literature review to identify all factors that might affect VC contracting.[9] In their seminal work, Tyebjee and Bruno (1984) indicate that VC financing follows a well-defined process — starting from deal origination and ending with an "exit" from the investment. During this process, the start-up evaluation is among the most important and challenging tasks affecting both entrepreneurs and venture capitalists.

The typical VC firm appraises each start-up based on multiple criteria, e.g. the team's human capital, the innovative potential of the business idea. Moreover, the valuation of VC firms may be based on some expected rate of return, which will in turn depend on factors such as the industry, the investment stage, the macroeconomic environment (Manigart *et al.*, 2002). Silva (2004) concludes that VCs primarily focus on the entrepreneurs, the business idea, its sustainable advantages and growth potential. Hence, according to Silva (2004), the financial projections of the enterprise do not seem to play a central role in the selection of early-stage projects.

Dittmann *et al.* (2004) note that VCs typically employ multiple valuation methods during the evaluation process, so as to reduce the failure rate of funding agreements between the two parties. In this respect, Knockaert *et al.* (2010) identify three main screening profiles: a first, focussing on the technology; a second based on a finite set of factors such as ROI, projected growth and team synergies; a third that values most the underlying abilities of the entrepreneurs. The extensive review of Petty and Gruber (2011) thoroughly summarises this relevant research strand.

[8] For this reason, perfect separation of VC-backed from non-VC-backed start-ups is a key precondition to our work, as discussed in section 3.

[9] The modelling of the VC contract itself is beyond the scope of this work: interested readers can consult Kaplan and Strömberg (2003), Sørensen (2007), and more recently Ewens *et al.* (2018).

This leads to our stylised interpretation of the VC market's *modus-operandi*. Evidently, the set up of an investment agreement follows a set of conditions that motivate VC firms and start-ups to engage in the negotiation. On the supply side we find VC firms and their multiple evaluation criteria. On the demand side we find start-ups, which only seek VC if alternative more appealing financing channels are unavailable (Bertoni *et al.*, 2016). For example, if the start-up already disposes of free capital, or can easily access it either through its team or with the help of available collateral, it may not wish for additional VC investment. Finally, it will be easier or more difficult for the firm to raise finance depending on personal factors such as the founders' reputation, network and experience.

Our literature review justifies a distinction between two types of components of the VC contracting process. The first class of factors relates to high-level characteristics that set apart VC-investable start-ups. These "preconditions" — necessary for a company to constitute a viable VC investment opportunity — shape the boundaries of the set $\mathbf{M}_2$ introduced in Figure 1. We call these *discriminants* of VC financing and discuss them in section 4.2.1. A second subset of characteristics relates to additional determinants of VC financing as well as instrumental variables that affect either demand or supply of VC. In line with the literature, these factors are more likely to be "traded-off" in the investment appraisal process. We call these *predictors* and describe them in section 4.2.2.

Following the notation introduced in section 4.1, we can formalise our assumption as follows. The components $\mathbf{X}_\mathrm{j}$ of the assignment mechanism are further partitioned into:

$$\mathbf{X}_\mathrm{j} = \{\mathbf{H}_\mathrm{j}, \mathbf{Z}_\mathrm{j}\} \tag{5}$$

where $\mathbf{H}_\mathrm{j}$ and $\mathbf{Z}_\mathrm{j}$ are discriminants and predictors of VC financing respectively.

4.2.1 Discriminants of VC financing

The subset $\mathbf{H}_\mathrm{j}$ incorporates some principal characteristics framing the firm and its operations. One major criterion found to influence decisions is the market environment (Hisrich and Jankowicz, 1990) as well as the environmental threats to the business (Tyebjee and Bruno, 1984; Meyer *et al.*, 1993). Furthermore, non-financial strategic factors, such as the attractiveness of the industry (Miloud *et al.*, 2012) and the level of competition (Hutt and Thomas, 1985; Khan, 1987; Muzyka *et al.*, 1996) have been identified to significantly affect valuation.

To account for the above considerations, we include the start-up's country and sector in the subset $\mathbf{H}_\mathrm{j}$. The geographic location is linked to crucial factors, such as the legal framework, property laws, investment climate and other macroeconomic conditions. In addition, the sector often has a role in forming expectations for the investment return, business development time and product curve shape, among others.[10] In addition to these features, $\mathbf{H}_\mathrm{j}$ includes the age of the firm at investment, which also plays an important part in pinpointing the start-up's project trajectory and development phase.

Last but not least, Hutt and Thomas (1985), Khan (1987) and Hisrich and Jankowicz (1990) all find that the degree of product differentiation is an important VC investment criterion. Therefore, the subset $\mathbf{H}_\mathrm{j}$ is completed with the firm's technological edge, assessed through the firm's patent

[10] We identify a total of 18 sectors. For details about our industry classification approach, see Appendix A.

ownership and degree of innovativeness. Exploiting patents' role as signal for the development stage of the start-up's technology (Lemley, 2000; Haeussler *et al.*, 2014), we add to $\mathbf{H}_j$ a dummy variable that indicates whether the company had applied for at least one patent at the time of investment. The signalling function of patents helps overcoming potential endogeneity concerns — since the dummy's pre-treatment nature cannot be guaranteed at the year of investment.[11]

Conceptualising the start-up innovativeness proves a considerably harder task. We expect VC firms to assess the degree of innovativeness of a start-up by looking at the key features of its entrepreneurial strategy, i.e. how the start-up team wishes to achieve their vision. The strategic management literature defines this the "entrepreneurial orientation" (EO) of the start-up. EO is composed of policies and practices that allow to fulfil the start-up's *"organizational purpose, sustain its vision, and create competitive advantage(s)"* (Rauch *et al.*, 2009, p.761). High EO leads to high propensity towards innovative activities, risk taking and competitive proactiveness (Hult *et al.*, 2004). To facilitate our work, we assume that VC firms can only observe one of two levels of EO: *high* or *low*.

We approximate the entrepreneurial orientation of start-ups by means of their trade description — a short overview of their activity and strategy.[12] We then manually classify sentences from about 7,000 trade descriptions out of 23,027 randomly sampled treated and untreated start-ups. We use this data to train a deep learning algorithm — the residual Long Short-term Memory model (residual LSTM, He *et al.*, 2016). The fitted model is able to discern high from low innovativeness start-ups with an accuracy of about 90%. Finally, we use the model's predictions to "score" the innovativeness of start-ups on a percent scale. Refer to Appendix C for a detailed overview of the approach.

4.2.2 Predictors of VC financing

The second subset of firm characteristics, $\mathbf{Z}_j$, includes additional features that affect the assignment mechanism, mainly related to the entrepreneurial team. The latter is a recurrent theme in the VC valuation literature. Shepherd and Zacharakis (1999) and Macmillan *et al.* (1985a, 1987) highlight the importance of the entrepreneur's ability and track record. In their widely-cited studies, Macmillan *et al.* (1985a, 1987) include entrepreneurial experience and personality in five out of the top ten most important criteria in start-up valuation. More recently, Miloud *et al.* (2012) also find that the quality of the entrepreneurial team and the new venture's network significantly affect valuation.

Retrieving information about the entrepreneurial team from the Orbis database entails several challenges. Aside from considerable data loss, we have no precise indication on whether a member of the firm's management team is also a founder of the company. We thus resort to a proxy based on the timing of management roles vis-à-vis the firm's date of incorporation. We collect data for all contacts with management or board of directors (shareholder) roles who joined the firm within five (four) years of its incorporation date. Although our proxy may not perfectly identify the actual entrepreneurial team, it offers a highly correlated measure for the "initial conditions" of firms in terms of human capital endowment. Due to lack of detailed data on entrepreneurs in Orbis, we are also

[11] As VC firms can detect the presence of patentable technologies prior to the time of the investment, we assume patent applications submitted in the investment year to be factored in the VC firm appraisal process.

[12] Trade descriptions are compiled by Bureau Van Dijk. While the *third-party* nature of these short texts improves homogeneity and mitigates the risk of finding over-emphasised EOs, a drawback of this proxy is that it is occasionally vague and/or outright inadequate for our evaluation.

limited in the measures available to explore the human capital dimension of start-ups (i.e. we are restricted to observables like team size, founders' age, previous experience, gender and nationality).

We complete the set of predictors $\mathbf{Z}_j$ with two instrumental variables identifying exogenous sources of variation in the access to VC and/or financing alternative to VC. Both variables exploit the heterogeneity at the geographic level, an advantage brought by the pan-European nature of our dataset. Both additional measures leverage on functional urban areas (FUA) as the main geographical unit. FUAs consist of densely populated areas and their neighbouring commuting zones. They were first developed in OECD (2012) and further refined by the European Commission and OECD.[13]

The first instrument is a proxy for housing supply elasticity based on satellite imagery analysis. Robb and Robinson (2014) argue that in markets where supply is perfectly inelastic, housing demand shocks translate directly into price shocks. This renders the value of home equity highly sensitive to changes in housing demand, therefore a poor form of collateral to pledge against bank loans. Conversely, the collateral value of entrepreneurs located in areas with highly elastic housing supply is less likely to be affected by aggregate housing demand. To test this identifying assumption, the authors use a predictor of housing supply elasticity developed by Saiz (2010). The measure is constructed by processing satellite-generated data with geographic information system (GIS) techniques, deriving the share of developable land within 50-kilometer radii from metropolitan central cities.

Appendix D details our replication of Saiz's process to estimate the share of undevelopable land for the European case. Due to the lack of comprehensive and harmonised time series on house prices for most European FUAs, we were not able to fully replicate Saiz's work and estimate the housing supply elasticities. However, given the quasi-linear relationship between the estimated housing supply elasticity and the GIS-based variable in Saiz (2010), we chose to use the latter as a proxy.

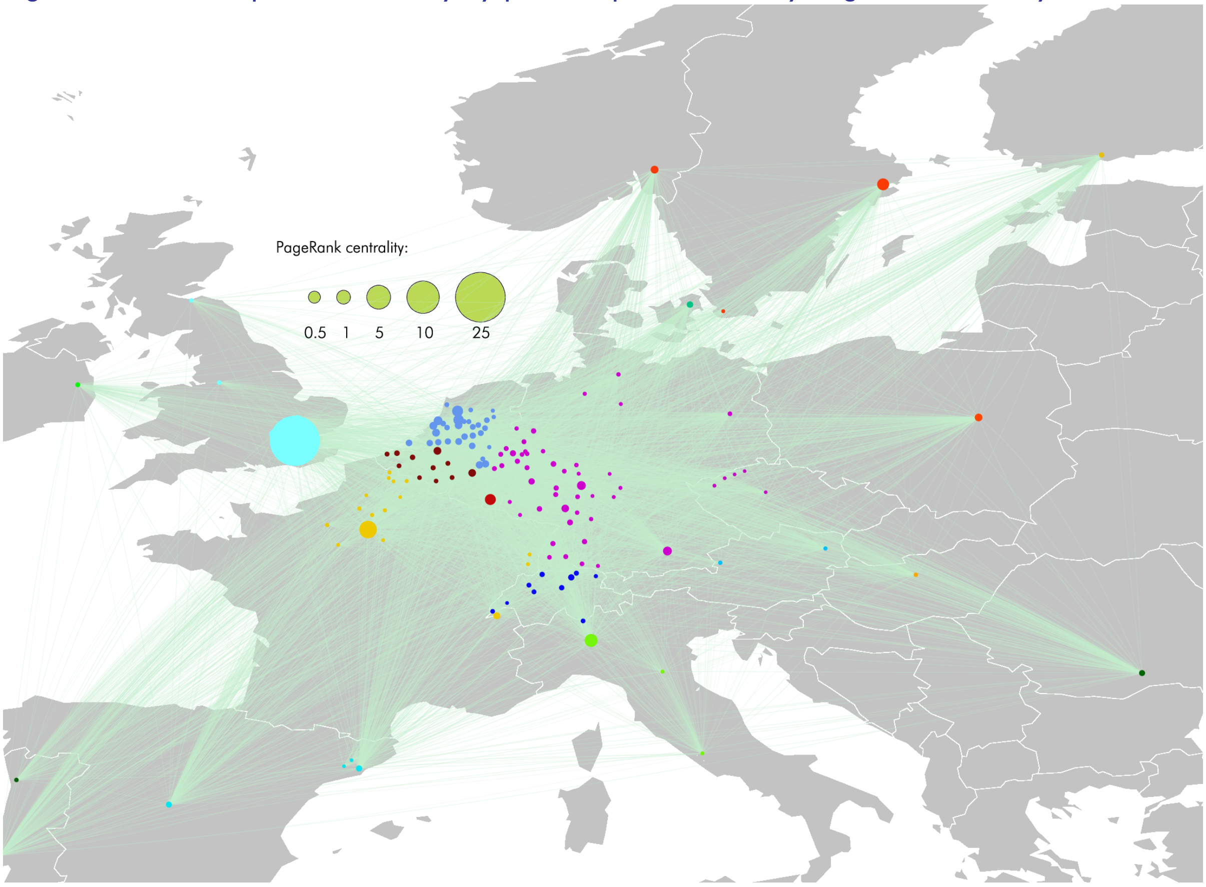
The second instrument is a proxy for the supply of venture capital. Lerner (1995) studies a sample of 271 biotechnology firms in the US receiving VC investments during 1978 and 1989, observing that geographic proximity is a key determinant of venture board membership. Bernstein *et al.* (2015) surveyed 306 VC investors, mostly US-based, finding that 9 out of 10 would increase their on-site involvement with a distant investee should a direct flight route be made available to them. Inspired by these stylised facts, we use network theory to derive a measure for the "accessibility" of start-ups with respect to the population of active VC firms. We model the European VC ecosystem as a network of VC "hubs" (represented by each and every FUA) connected by flights.[14] A given hub may be more or less "central" depending on a) the number of investors that can reach it via a direct flight, b) the number of flight routes that reach the hub, and c) its physical proximity/remoteness to other hubs.

Appendix E details the methodological steps to compute our measure of accessibility. We rank hubs according to their PageRank centrality index (Page *et al.*, 1998), which corresponds to the probability that a VC firm would land on the hub were it to move randomly across our network for a large amount of time. Figure 4 portrays the top 20% hubs by centrality. Finally, to account for the distance between the hub and the start-up, we compute a firm-specific index by imposing an exponential decay to the PageRank index: the larger the distance between the start-up's headquarters and the hub's access point, the less the start-up will be able to reap the benefits of its hub's centrality.

[13] See European cities – the EU-OECD functional urban area definition.

[14] We obtained flight routes data from OpenFlights.

Figure 4: Venture capital accessibility by plane: top 20% FUAs by PageRank centrality



4.3 Construction of the matching estimator

We implement the estimator of Abadie and Imbens (2006) via a combination of exact- and propensity score-based matching. Propensity score matching (Rosenbaum and Rubin, 1983) is a non-parametric estimator of causal effects that is widely used in the evaluation literature. It addresses the limits of least square analysis in the presence of observational data, while it also avoids the so-called *curse of dimensionality*, significantly restricting the feasibility of matching estimators.

To maximise our model's predictive ability, we carry out this analysis on the entire set of European VC-backed firms, i.e. the 4,945 early stage firms discussed in Table 1. Our two-step matching approach mirrors the stylised treatment assignment process discussed in section 4.2: start-up j is first screened based on characteristics $\mathbf{H}_j$, while the investment decision considers the full set of pre-investment attributes, i.e. $\mathbf{H}_j$ and $\mathbf{Z}_j$. Following the notation of section 4.1, we can formalise this as follows:

$$\Pr\left(W_j \mid \mathbf{X}_j = \mathbf{x}\right) = \begin{cases} e\left(\mathbf{H}_j, \mathbf{Z}_j\right) & \text{if} \quad h\left(\mathbf{H}_j\right) = 1 \\ 0 & \text{if} \quad h\left(\mathbf{H}_j\right) = 0 \end{cases} \tag{6}$$

where $e\left(\mathbf{H}_j, \mathbf{Z}_j\right)$ is the propensity score and $h\left(\mathbf{H}_j\right)$ indicates whether start-up j is "VC-investable".[15]

[15] The following notation, in line with Figure 1, is thus equivalent to Equation 6:

$$\Pr\left(W_j \mid \mathbf{X}_j = \mathbf{x}\right) = \begin{cases} e\left(\mathbf{X}_j\right) & \text{if} \quad j \in M_2 \\ 0 & \text{if} \quad j \notin M_2 \end{cases}$$

To narrow down the initial pool of counterfactual candidates from the Orbis database, we stratify treated companies by sector and year of investment. This generates 137 unique strata (131 EIF-specific). A control candidate for a given stratum must satisfy the early stage conditions as set forth in Appendix B. To optimise the identification of counterfactuals — and without loss of generality — we impose two additional restrictions that improve data coverage. First, we only consider firms with available business description data — these are necessary to estimate the innovativeness score as discussed in section 4.2.1. Second, we only sample companies with available financial account data for at least one year following the year of investment in the respective stratum. In the case of some strata, this leads to more than a million candidates found. To facilitate our data work, we randomly sample up to 42 control candidates per treated firm in the stratum to feed into our further analyses.

We first carry out an exact matching based on $\mathbf{H}_j$, i.e. country, aggregate sector, patent ownership, age and innovativeness. Since age and innovation score are continuous variables, exact matching is impractical and is replaced with a "rolling-window" matching.[16] The analysis of the age distribution at investment date reveals significant clustering of companies around specific age values: this suggests the presence of structural breaks in the way age-related factors (e.g. business development stage) affect treatment propensity. For this reason, we imitate this pattern in the age intervals we use for matching, with progressively longer intervals applied to older companies.[17] The design of the innovation score intervals follows a different logic: to incorporate the uncertainty in the assignment of innovativeness scores (see Appendix C), we allow for a wider range in the score interval 30%-70% compared to predicted scores laying at both extremities of the distribution.[18]

The second step of our matching approach entails the construction of a propensity score model. In this phase, we pool together the set of characteristics $\mathbf{H}_j$ and $\mathbf{Z}_j$ to estimate treatment probability. The wide mix of factors that contribute to the assignment mechanism brings in considerable challenges to our identification strategy. This happens, for instance, in the case of attributes of the start-up team, many of which are unobservable to us. To compensate for these empirical constraints, we exploit the geographic breadth and the clustered nature of our dataset to model the unobserved heterogeneity. The strategy also improves the model's ability to represent our data, which is organised hierarchically: at the lowest level we find the entrepreneur i, nested within start-up j, itself nested within FUA k. Figure 5 provides a visual illustration of the hierarchical nature of our data.

Start-ups located in the same urban area are likely to share many of the advantages (and pitfalls) related to access to VC financing (see e.g., Reynolds and Storey, 1993; Cooper and Folta, 2000). Jaffe *et al.* (1993) also show that location plays a role in the access to scientific knowledge, technological expertise and specialised suppliers. As a result, we estimate our propensity score using a two-level random coefficient model for start-up j located in FUA k. The random intercept of FUA k should capture several of the unobserved effects described above.[19] In addition, we include a random coefficient for

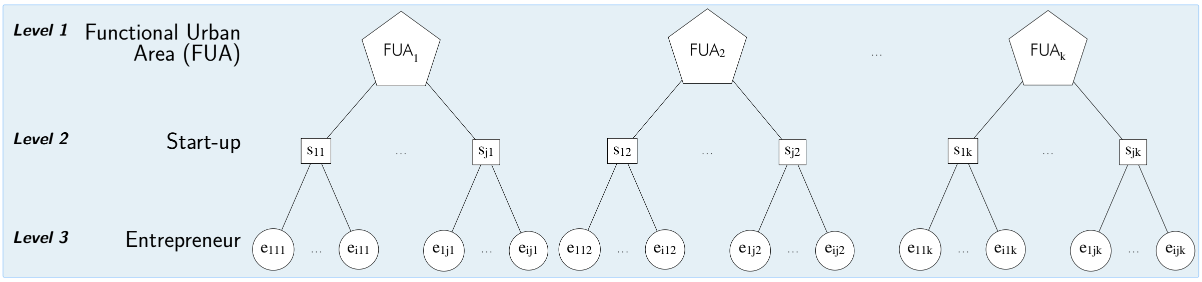
[16] We select controls falling within a window centered around the age/innovation score of each treated firm.

[17] The precise age range-matching interval pairs we used are as follows (values in years) — 0-2.99: ±0.5; 3-4.99: ±1; 5-6.99: ±1.5; 7-8.99: ±2; 9+: ±3.

[18] The precise innovativeness range-matching interval pairs we used are as follows — 0-0.150 and 0.851-1:±0.05; 0.151-0.300 and 0.710-0.850:±0.1; 0.310-0.700:±0.15.

[19] Note that this violates one important assumption of random effect models, i.e. that the random intercept is uncorrelated with other observed covariates. To avoid estimation bias, we follow the approach in Skrondal and Rabe-Hesketh (2004) and include FUA-level means as covariates in our propensity score regression.

Figure 5: Multi-level structure of the data



the foreign-born status and the previous founding experience of entrepreneurs, allowing their slope to vary between FUAs. This is motivated by the fact that, e.g. the effect of being foreign-born on the likelihood to obtain VC financing may be different in, say, a highly international city compared to urban areas with a lower openness to foreign capital and labour.

One additional challenge addressed by our multilevel design is the need to predict a group-level outcome, i.e. VC financing, using a set of individual-level characteristics (e.g., age, gender of founders). A straightforward solution is to use average values for the entrepreneurial team to predict treatment status. However, Croon and van Veldhoven (2007) show that this approach leads to biased estimates, particularly when group sizes are small. For this reason, we follow instead the two-step approach of Griffin (1997): in the first step, we fit each individual-level covariate on firm- and FUA-level random effects and all other founder attributes. To predict treatment status, we then use Empirical Bayes estimates of the firm- and FUA-level random effects from each first stage regression.[20]

Table 2 reports the odds-ratios and goodness of fit of our propensity score model. All main covariates in our model are either significant or strongly significant, with the direction of their effect also in line with the literature discussed in section 4.2. One important exception to this rule is the effect of our proxy for the value of home equity: a higher degree of housing supply restrictions, linked to a more volatile home equity market, points to a lower rate of VC contracting. This finding contradicts the channel between VC financing and house supply restrictions observed by Robb and Robinson (2014) for the US case. Simple descriptives are sufficient to prove that European early stage start-ups tend to cluster around areas with higher shares of developable land. Nevertheless, we are persuaded to keep this variable in our baseline model specification, as it ultimately improves its predictive ability.

Following the literature, we saturate our model by means of higher level effects as well as several two-way interactions. We use the model's predicted scores to identify the counterfactual firm for every invested start-up via a one-to-one nearest-neighbour matching with replacement and calliper. This entails matching each treated firm to the control with the closest propensity score where the distance between the two does not exceed a certain pre-determined statistic, i.e. the calliper. We use a calliper of 75% of the standard deviation of the treated companies' propensity scores. The replacement

[20] Formally, we rearrange our predictors of VC financing to account for the multilevel nature of our data: $\mathbf{Z}_{ijk} = \{\mathbf{r}_k, \mathbf{w}_{jk}, \mathbf{z}_{ijk}\}$. We then estimate the propensity score using a two-step approach. We first fit each founder-level variable $z_{v,(ijk)}$ on all other founder-level covariates, firm- and FUA-level random effects:

$$z_{v,(ijk)} = \delta_0 + \delta' \mathbf{z}_{-v,ijk} + \upsilon_{v,k} + \omega_{v,jk} + \varepsilon_{ijk} \quad \forall v = 1, 2, \dots, V$$

We then plug the empirical Bayes estimates $\widehat{\upsilon}_{v,k}$ and $\widehat{\omega}_{v,jk}$ into our multi-level propensity score model:

$$\text{logit}\left(e\left(\mathbf{X}_{jk}\right)\right) = \gamma_{00} + \beta' \mathbf{H}_{jk} + \gamma_0' \mathbf{r}_k + \theta' \mathbf{w}_{jk} + \varphi' \left(\widehat{\boldsymbol{\upsilon}}_k + \widehat{\boldsymbol{\omega}}_{jk}\right) + \zeta_{0k} + \eta_{jk} \tag{7}$$

Table 2: Propensity score matching multi-level model. Dependent variable is treatment status.

	$\Pr(\text{treatment} = 1)$
	(1)
	MULTI-LEVEL MIXED EFFECTS LOGIT
Founding team size‡	1.9633***
	(0.085)
Age of founding team‡	0.9459***
	(0.009)
Previous founding experience‡	2.9483***
	(0.945)
Foreign-born entrepreneurs‡	0.8648***
	(0.029)
Female entrepreneurs‡	0.1309***
	(0.031)
Firm's age at inv. year	0.9562**
	(0.014)
Firm holds patent at inv. year	2.8860***
	(0.433)
Predicted degree of innovation	1.7366**
	(0.320)
Firm's accessibility	1.2892†
	(0.178)
$\ln$ (Firm's distance from closest FUA's centroid)	0.8813***
	(0.010)
$\ln$ (FUA's undevelopable land)	0.4584†
	(0.213)
Constant	0.0026***
	(0.002)
Cluster means (pooled)	12.7471*
	(13.928)
Quadratic terms (pooled)	0.0029***
	(0.003)
Cubic terms (pooled)	1.8675
	(2.591)
Interactions (pooled)	0.7591
	(0.908)
Investment Year FEs	Yes
Start-up macro-industry FEs	Yes
Start-up macro-region FEs	Yes
Log-likelihood	-6,613.27
Obs.	32,264
Pseudo-R^2 (McKelvey and Zavoina, 1975)	0.38
Area under the ROC curve	0.858

† 0.10 * 0.05 ** 0.01 *** 0.001; ‡ Founder-level characteristic; Exponentiated coefficients (odds-ratios).

option allows counterfactuals to be potentially paired with multiple treated firms, trading efficiency for consistency (Caliendo and Kopeinig, 2008). To mitigate data loss, we prioritise control candidates with non-missing outcomes at the treatment year. This implies that final matched samples could slightly differ across outcome variables. Table 3 provides descriptive statistics of pre-treatment attributes in the final matched sample for the case of total assets, differentiating between treatment and control group — T and C respectively. Column (5) of Table 3 provides the p-value of mean-comparison t tests for each included variable, showing the high balancing ability of our estimator.

Table 3: Descriptive statistics of PSM model and balancing checks

	Obs. (1)		Mean (2)		Median (3)		St. dev. (4)		P-value (5)
	T	C	T	C	T	C	T	C	T/C
Average team age at founding	286	286	41.15	42.18	41.15	43.50	8.309	8.111	0.135
Share of female team members	286	286	0.10	0.11	0.00	0.00	0.189	0.203	0.620
Share of foreign team members	286	286	0.16	0.14	0.00	0.00	0.265	0.282	0.453
Average team prev. experience	286	286	40.86	60.37	2.00	1.33	425	402	0.574
Team size	286	286	4.44	4.13	3.00	3.00	3.463	3.407	0.279
Company age at inv. year	286	286	1.95	1.95	1.00	1.00	2.154	2.154	1.000$^{\varphi}$
Patent at investment year	286	286	0.26	0.26	0.00	0.00	0.437	0.437	1.000$^{\varphi}$
Innovativeness score	286	286	0.59	0.59	0.92	0.92	0.437	0.436	0.987
Company accessibility score	286	286	1.19	1.07	0.44	0.31	1.641	1.601	0.348
ln (distance from FUA's centroid)	286	286	-0.69	-0.80	-2.30	-2.30	2.344	2.377	0.563
ln (undevelopable land)	286	286	-2.98	-2.92	-3.43	-3.30	0.997	1.044	0.479
Investment period:									
2007-08‡	286	286	0.26	0.26	0.00	0.00	0.437	0.437	1.000$^{\varphi}$
2009-11‡	286	286	0.24	0.24	0.00	0.00	0.431	0.431	1.000$^{\varphi}$
2012-14‡	286	286	0.50	0.50	0.50	0.50	0.501	0.501	1.000$^{\varphi}$
Macro-sector:									
ICT‡	286	286	0.50	0.50	0.50	0.50	0.501	0.501	1.000$^{\varphi}$
Life Sciences‡	286	286	0.20	0.20	0.00	0.00	0.403	0.403	1.000$^{\varphi}$
Services‡	286	286	0.17	0.17	0.00	0.00	0.374	0.374	1.000$^{\varphi}$
Other‡	286	286	0.13	0.13	0.00	0.00	0.336	0.336	1.000$^{\varphi}$
Macro-region:									
DACH‡	286	286	0.27	0.27	0.00	0.00	0.446	0.446	1.000$^{\varphi}$
Nordics‡	286	286	0.11	0.11	0.00	0.00	0.311	0.311	1.000$^{\varphi}$
France & Benelux‡	286	286	0.07	0.07	0.00	0.00	0.261	0.261	1.000$^{\varphi}$
South & CESEE‡	286	286	0.07	0.07	0.00	0.00	0.249	0.249	1.000$^{\varphi}$
UK & Ireand‡	286	286	0.48	0.48	0.00	0.00	0.500	0.500	1.000$^{\varphi}$

Note: our final matched samples are specific to each outcome, with results above related to total assets. Results for other outcomes are very similar. ‡ dichotomic variable; $^{\varphi}$ exactly matched.

5 Results

In this section, we discuss the estimated average treatment effect on the treated (ATT) for several key performance indicators (see Appendix F for definition and glossary). Each ATT is estimated in a regression setting, which allows for additional controls to remove any residual imbalance. We also deflate all monetary values using harmonised country- and NACE Rev. 2 sector-level producer price indices (collected from Eurostat). Table 4 shows descriptive statistics of our main outcome variables.

Table 4: Descriptive statistics of outcome variables at the year of treatment

	Obs. (1)		Mean (2)		Median (3)		St. dev. (4)	
	T	C	T	C	T	C	T	C
ln(Capital)	197	253	1.81	0.59	2.59	1.44	3.652	3.981
ln(Total assets)	200	261	6.68	4.28	6.81	4.90	2.105	3.731
ln(Turnover)	80	95	4.50	5.32	4.87	5.34	2.962	2.865
ln(Costs)	70	83	6.54	6.04	6.62	6.07	1.983	2.600
ln(Staff Costs)	67	67	5.64	5.72	5.73	5.61	2.265	2.090
ln(Staff Number)	76	74	1.96	2.15	1.95	1.79	0.995	1.320

5.1 Economic size of start-ups

Table 5 reports the ATTs up to five years following a VC investment. ATTs are based on the logarithm of each financial indicator, thus representing the instantaneous change in the rate of growth due to

Table 5: Estimated ATTs on economic size, by post-treatment period.

	ln (Capital) (1)	ln (Tot. assets) (2)	ln (Revenues) (3)	ln (Op. costs) (4)	ln (Staff costs) (5)
	OLS	OLS	OLS	OLS	OLS
$ATT_{t=0}$	1.4650***	2.4766***	-0.5393	1.1644***	0.8954**
	(0.301)	(0.253)	(0.353)	(0.263)	(0.300)
$ATT_{t=1}$	1.2895***	1.9001***	0.1855	1.4879***	0.7115*
	(0.293)	(0.228)	(0.307)	(0.282)	(0.291)
$ATT_{t=2}$	1.3205***	2.0081***	0.9179**	1.6146***	1.2148***
	(0.310)	(0.231)	(0.313)	(0.330)	(0.289)
$ATT_{t=3}$	1.6243***	1.9396***	0.8214*	1.4914***	1.0373**
	(0.368)	(0.283)	(0.375)	(0.388)	(0.346)
$ATT_{t=4}$	2.0124***	2.2051***	0.7966*	1.8046***	0.9825**
	(0.443)	(0.289)	(0.383)	(0.374)	(0.344)
$ATT_{t=5}$	2.0534***	2.3258***	0.9740†	2.3590***	0.8114†
	(0.523)	(0.407)	(0.508)	(0.675)	(0.466)
N° of observations	2,416	2,465	1,254	1,044	953
N° of firms	524	528	372	299	274
N° of treated	255	258	160	132	126
T-test on PS (p-value)	0.222	0.212	0.095	0.164	0.146

† 0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets.

a shift in the treatment status (i.e. treated/untreated).[21] For instance, the ATT for start-up capital in the treatment year — coefficient $ATT_{t=0}$ in column (1) of Table 5 — shows that the average capital level for EIF-backed start-ups stands at 147 % the level of non-VC-backed start-ups.

Column (1) of Table 5 shows that EIF-supported start-ups tend to be one to two times more capitalised than their counterfactuals. Moreover, the spread between the two groups widens over time. Similarly, column (2) reports a significant effect of EIF-backed VC on start-up assets, once again about two times larger than the control group.

One might argue that growth in assets, equity and to some extent liabilities[22] is merely the result of our counterfactual approach. After all, we compare a group of EIF-backed start-ups against firms that did not receive VC investments.[23] This argument justifies attempting to decompose our treatment effect, to disentangle *direct* growth from additional, *indirect* growth — both induced by the treatment.

To separate "direct" from "indirect" treatment effects of VC, we re-estimate our regression on assets after deducting from the dependent variable the amount of VC investment received.[24] Results from this supplementary analysis show that in period $t = 0$ the treatment dummy is not significant, i.e. the average difference between treated and controls is entirely explained by the amount of VC investment received. However, from period $t = 2$ onwards treated companies show significantly higher levels of "net" assets than their counterfactual. This positive and significant difference, not directly explained

[21] To mitigate the incidence of outliers, we winsorise each outcome indicator at the 1st and 99th percentile.

[22] Not all VC investments necessarily translate into capital injections. For example, VC firms could opt for a convertible loan, representing a liability in the start-up's balance sheet (at least until conversion).

[23] Note, however, that this argument does not invalidate our baseline ATTs: under our identifying assumptions, our estimates are not affected by bias, since the treated company would not have been able to make up for the "lost" EIF-backed investment through other financing means.

[24] By construction, the amount of growth for control start-ups that is explained by the VC investment is zero. Results from this supplementary analysis are not shown but available upon request.

by the amount of VC investment received, indicates that the "size" effect of VC financing extends above and beyond the amount of investment itself.

Column (3) of Table 5 reports the estimated treatment effects on revenues. The increase in funding brought by VC financing further propagates through the start-up's production function, positively affecting turnover levels for the treated. However, the magnitude of the effect is lower compared to the reported coefficient on assets, ranging from 19 % one year after treatment up to 97 % five years after treatment. Moreover, no significant effect can be observed until the second year after treatment. Significance levels for treatment effects on revenues are higher than in other firm size indicators,[25] hinting at the presence of large variations across start-ups.

Column (4) of Table 5 presents the treatment effects on operating costs. Operating costs portray yet another dimension of company size, pertaining to the financial "firepower" of start-ups to acquire key production inputs. Against this background, VC financing translates into additional liquidity for treated start-ups, which in turn explains the divergent pattern of spending for treated relative to controls. The magnitude of the effect on costs outweighs the effect on revenues, ranging from one to two times higher expenses for treated than controls. This suggests that VC-backed start-ups trade off short- to medium-term profitability to achieve the desired scale of operation. See section 5.3 for further evidence on profitability patterns.

We conclude our analysis of the effect of VC on start-up size with column (5) of Table 5, presenting the treatment effects on employment costs. Labour costs is our proxy of choice to track employment growth: this measure is better suited to capture changes in full-time equivalent labour than a crude headcount. Moreover, headcount figures in the Orbis database are rarely harmonised and often outdated.[26] We control for potential systematic changes in salaries unrelated to job creation by including country- and industry-level effects both in the matching and the ATT estimation phase. Compared to counterfactuals, staff costs are about 100% higher for treated firms following the VC investment. Note that this effect could be driven by a raise in the headcount and/or an increase in salaries. To disentangle the two potential drivers of aggregate wage growth, we compute the ATTs on average wages, i.e. staff costs divided by headcount. Despite their point estimates being positive (+25% on average), ATTs on average wages are not significant in all but period $t = 3$, where the difference is weakly significant. We conclude that the positive effect on start-up staff costs most likely indicates that VC financing supported by the EIF spurs employment growth in start-ups.

Overall, the findings shown in Table 5 are consistent with the literature studying the impact of VC investment we briefly discussed in section 2 (Alemany and Martí, 2005; Engel and Keilbach, 2007; Peneder, 2010; Puri and Zarutskie, 2012). Our analysis confirms venture capital's positive effects on a diverse set of firm size metrics as well as across a broad geographic spectrum focussing on EU28. While the nature of our data does not allow to go into further detail and evaluate the specific transmission channels through which VC financing affects start-ups, most studies conclude that a combination of factors are at play, including (but not limited to) the provision of capital, valuable managerial advice, and access to a network of experts and service providers affiliated to the VC firm.

[25] The results are, however, robust to different model specifications, assumptions about the error structure, as well as stricter matching criteria. For instance, the baseline results hold if we implement a stricter calliper matching, which yields a better balanced sample (p-value 78.9%) at the cost of 34% data loss.

[26] Nevertheless, ATTs on headcount remain positive and significant, in line with our main result on staff costs.

5.2 Financial structure of start-ups

We now examine the causal effect of VC financing on the financial structure of start-ups. We use a set of sub-items of the assets and liabilities of start-ups to investigate the role of VC financing *vis-à-vis* the financial structure decisions of new firms. In turn, the analysis will shed further light on the findings of section 5.1. Of particular relevance is whether the growth-accelerating effect of VC financing is linked to a different mix of liquid and illiquid assets and/or internal and external financing. Table 6 shows the estimated ATTs on four different ratios based on asset components.

Table 6: Estimated ATTs on asset allocation, by post-treatment period.

	Cash over tot. assets (1)	Quick ratio[a] (2)	Tangible over tot. assets (3)	Intangible over tot. assets (4)
	GLM	TOBIT	GLM	GLM
$ATT_{t=0}$	0.1609***	0.0988***	-0.0573***	-0.0813***
	(0.030)	(0.029)	(0.017)	(0.024)
$ATT_{t=1}$	0.0936**	0.0749**	-0.0502**	-0.0510*
	(0.030)	(0.026)	(0.017)	(0.025)
$ATT_{t=2}$	0.0874**	0.0716*	-0.0508**	-0.0418†
	(0.030)	(0.030)	(0.017)	(0.025)
$ATT_{t=3}$	0.1100**	0.0380	-0.0394*	-0.0657*
	(0.034)	(0.036)	(0.020)	(0.030)
$ATT_{t=4}$	0.1018**	0.0427	-0.0258	-0.0523†
	(0.037)	(0.040)	(0.021)	(0.029)
$ATT_{t=5}$	0.0999*	0.0206	-0.0094	-0.0681†
	(0.046)	(0.046)	(0.028)	(0.035)
N° of observations	2,194	2,050	2,027	2,025
N° of firms	487	476	448	448
N° of treated	250	245	241	241
T-test on PS (p-value)	0.177	0.311	0.143	0.143

† 0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets; [a] see Appendix F for its definition.

Columns (1) and (2) of Table 6 report the treatment effects on two measures of financial liquidity: cash over total assets and the quick ratio, i.e. the share of current liabilities covered by current assets net of stocks. Both ratios pick up on the liquidity shock brought by VC. While the VC-induced cash surplus still persists in the medium run, the overall liquidity imbalance is absorbed over time, used by treated start-ups to fuel their scaling up. In response to the liquidity surplus, columns (3) and (4) of Table 6 document the relative short-run decrease of treated start-ups' reliance on fixed assets. At the same time, column (4) shows that VC investments do not artificially inflate the relative importance of intangibles that, if anything, lowers as a reaction to the liquidity boost.

Table 7 contains the treatment effect of VC on five liability and equity ratios. Expectedly, the VC investment generates a temporary imbalance that favours equity over liabilities — columns (1) and (2) in Table 7. The trade-off affects short-term, but not long-term liabilities — columns (3) and (5) respectively. The VC-driven rise in equity and simultaneous fall in short term liabilities hint to a substitution effect between the two financing options. However, the two observable sub-items of short term debt (short term financial loans and trade credit) are not affected by the treatment status. In fact, column (4) in Table 7 shows that the relative fall in current liabilities is due to the deficit in a mix of short term obligations comprising deferred items — e.g., revenue, tax, wages.[27]

[27] We exclude any effect from intra-group loans — which would also fall under this catch-all category — as complex corporate groups are not common among start-ups.

Table 7: Estimated ATTs on the financing mix, by post-treatment period.

	Equity over tot. assets (1)	Equity over tot. liabilities (2)	Current liab. over tot. assets (3)	Other current liab. over tot. assets (4)	Non-current liab. over tot. assets (5)
	GLM	GLM	GLM	GLM	GLM
$ATT_{t=0}$	0.1408***	1.0530***	-0.1244***	-0.1588***	-0.0114
	(0.036)	(0.170)	(0.032)	(0.035)	(0.032)
$ATT_{t=1}$	0.1554***	0.8620***	-0.1497***	-0.1759***	-0.0007
	(0.036)	(0.151)	(0.032)	(0.033)	(0.034)
$ATT_{t=2}$	0.0883*	0.5828***	-0.0905**	-0.1452***	0.0062
	(0.037)	(0.155)	(0.033)	(0.037)	(0.036)
$ATT_{t=3}$	0.0779†	0.3933*	-0.0589	-0.1259**	0.0060
	(0.042)	(0.175)	(0.041)	(0.043)	(0.044)
$ATT_{t=4}$	0.0209	0.1424	-0.0635	-0.1572**	0.0503
	(0.048)	(0.186)	(0.047)	(0.050)	(0.047)
$ATT_{t=5}$	0.0252	0.1828	-0.0439	-0.1258*	0.0272
	(0.052)	(0.225)	(0.056)	(0.056)	(0.051)
N° of observations	2,442	2,356	2,441	2,005	2,410
N° of firms	525	509	525	462	521
N° of treated	258	254	258	245	258
T-test on PS (p-value)	0.214	0.214	0.214	0.748	0.204

† 0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets.

The finding leads to a hypothesis that could characterise start-ups in the absence of VC. That is, non-treated start-ups might be relying on the support of "cornerstone" customers, who advance payments for products (services) that are not yet ready for delivery (provision).[28] In light of this, control start-ups would fuel their go-to-market strategy through the relative surplus of unearned revenues. Treated start-ups, by tapping into the VC financing to sustain the development and marketing of their products and services, can reduce the need to adopt this business strategy. We leave it to future research to confirm this dynamic, as our data cannot precisely identify the source of the substitution effect.

In the medium run, treated start-ups tend to rely on long-term debt financing to the same extent as their counterfactuals. Against the backdrop of relatively lower shares of fixed assets (as shown in Table 6), hence collateral, treated start-ups are able to secure a medium-run mix of external financing sources that is comparable to control firms. One possible explanation to this finding is the signalling effect of VC investments towards the solvency and (long term) profitability of treated start-ups.

However, we could also be tracking a change in the preference of start-uppers. On the assumption that VC-backed start-ups are set on a path to follow-on VC investments, entrepreneurs may privilege the receipt of non-equity or hybrid instruments, so as not to over-dilute the start-up's capital base. Finally, we could also be observing a shift to debt-type financing as a response to a shortage of supply of follow-on investments. Once again, we lack sufficient evidence to pinpoint the exact dynamics at play, so we leave it to future research to explore this subject further.

5.3 Profitability of start-ups

In this section, we take a brief look at the effects of VC investments on start-ups' short-to-medium term profits. Table 8 lists ATTs for a series of profit-related metrics. One technical issue with profit

[28] First time customers may be attracted by e.g., loss-making prices (until the start-up operates at scale).

Table 8: Estimated ATTs on profitability, by post-treatment period.

	nl (ROA)	nl (ROE)	Pr (pre-tax profit ≥ 0)	ln (Negative pbt)	ln (Positive pbt)
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	PROBIT	ENDOGENOUS SWITCHING OLS	
$ATT_{t=0}$	-0.4588***	-0.8972***	-0.3525***	1.8888***	1.4408
	(0.109)	(0.178)	(0.042)	(0.310)	(1.370)
$ATT_{t=1}$	-0.7484***	-0.8934***	-0.3624***	2.2043***	0.9975
	(0.105)	(0.211)	(0.052)	(0.384)	(1.291)
$ATT_{t=2}$	-0.5262***	-0.6877**	-0.3050***	2.2242***	1.4846
	(0.107)	(0.223)	(0.056)	(0.400)	(1.205)
$ATT_{t=3}$	-0.3986**	-0.7186**	-0.2252**	1.9978***	1.2902
	(0.126)	(0.238)	(0.075)	(0.423)	(0.974)
$ATT_{t=4}$	-0.2362	-0.0586	-0.1255	2.7185***	1.2629
	(0.164)	(0.278)	(0.088)	(0.421)	(1.054)
$ATT_{t=5}$	-0.0504	-0.0624	-0.1735	1.2550***	1.2800
	(0.256)	(0.351)	(0.108)	(0.373)	(1.147)
N° of observations	1,194	1,202	1,204	1,143	
N° of firms	326	326	327	313	
N° of treated	144	144	144	142	
T-test on PS (p-value)	0.160	0.157	0.162	0.162	

† 0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets.

measures is their very skewed distribution, stretching towards both the negative and positive domain. To address this issue without sacrificing sample size, we use a *neglog*-type transformation (Whittaker *et al.*, 2005).[29] A drawback of this solution is that the resulting coefficients are not comparable to those from log-linear models. We thus refrain from assigning value to the magnitude of some results.

Before discussing the results of Table 8, it is important to mention that average and median values for profits are mostly negative for both groups over the measured time window. For instance, the average control start-up bears a financial loss of EUR 0.18m in period $t = 0$ and EUR 0.18m in period $t = 4$. Nevertheless, VC-backed start-ups sustain much larger average losses (from EUR 1.17m in period $t = 0$ to EUR 3.60m in period $t = 4$), also against the backdrop of their significantly larger size. Short-to-medium term financial losses are thus the norm for young and highly innovative start-ups, a finding in line with our prior hypothesis that significant growth may be necessary prior to reaching scale-driven cost efficiency.

VC-backed start-ups appear to trade off short-to-medium term profitability against achieving the desired scale of operations. Columns (1) and (2) of Table 8 show that short-term return on assets and return on equity are negatively impacted by VC investments. However, the effect is not significant after period $t = 4$ and, most importantly, the magnitude decreases over time, hinting to treated start-ups "catching-up" with control firms in the medium term. Similarly, column (3) of Table 8 shows that, while treated firms remain more likely to report negative profits throughout the analysed time window, the spread narrows over time.[30]

29 This is defined as:

$$\mathrm{nl}(x) = \begin{cases} -\ln(1 - x \cdot \xi) & x \leq 0 \\ \ln(1 + x \cdot \xi) & x > 0 \end{cases}$$

where $\xi = \ln(10)$ renders $\mathrm{nl}(x)$ approximately linear in the region near 0 (Webber, 2012).

30 We should disclaim here the potential confounding role of survivorship bias, caused by default rates affecting disproportionately more the start-ups that incur large losses. On this basis, some of our results could be driven by loss-making control start-ups exiting the sample more often than treated firms.

If our interpretation that VC investments enable start-ups to prioritise long-term growth over short-term profitability is correct, one outstanding question is whether VC financing itself entails a decline in financial discipline for beneficiary entrepreneurs. To investigate whether e.g., agency problems affect profit levels of VC-backed firms, we estimate the ATT separately for non-negative and negative profits. Should VC financing spur moral hazard, we would expect lower levels of earnings both for loss- and profit-making start-ups. One issue with this approach is, however, that start-ups can self-select into either sample, endogenously determining the profit "regime". Therefore, we estimate columns (4) and (5) of Table 8 using a two-step approach that first models the "switching" into either regime, then estimates the treatment effect in each sample (van der Gaag and Vijverberg, 1988).[31]

We find that VC financing increases the level of financial losses, but does not significantly reduce the level of financial gains — columns (4) and (5) in Table 8 respectively. The conclusion of this analysis is that, while VC-backed growth does lead to a trade-off in short-to-medium term profitability, there are no apparent cost inefficiencies brought by the VC financing itself. Once the loss-making or profit-making strategy is set, VC investments merely enable treated firms to sacrifice "more" short-term profitability than they could have otherwise had.

5.4 Moderating effects

We conclude our results analysis by discussing whether start-up characteristics shape the direction and size of our estimated ATTs. Table 9 displays the conditional treatment effects of VC investments by start-up attribute.[32] We focus here only on the economic size variables explored in section 5.1. Overall, our main results are maintained across groupings and most statistical tests do not detect significant deviations in ATTs among sub-classes. We discuss here some noteworthy exceptions.

We do not observe significant differences in the ATTs across investment periods. While point estimates of the ATTs may slightly differ for certain investment cohorts, the high variation and relatively small sample sizes do not allow us to detect meaningful deviations. The exception to this rule is the significant difference in terms of costs and staff costs for most cohorts compared to the 2012-14 period. This is most likely due to the censoring of the time series affecting the last cohort (the last observed year in our data is 2016).

Similarly, the sectoral breakdown does not lead to any meaningful and statistically significant divergence. The sole exception is the ATT on turnover, significantly higher in "Other sectors" than life sciences (the difference is also weakly significant in favour of ICT). These differences point out to the different business strategy in the life sciences industry, where the higher development costs cause the revenue-generating stage to take comparatively longer to materialise.

We do not detect a high number of meaningful deviations across innovation and age groups. We do find some limited evidence that less innovative start-ups (i.e., with predicted innovativeness score below 30%) benefit more than highly innovative companies — still positively impacted by VC investments — in terms of assets and employment growth. This mostly hints to the important role that

[31] We model the probability of switching to the non-negative profit regime with a series of geographical and sectoral dummies, age, innovativeness, treatment status, and capital levels.

[32] We fit a separate model for every moderating and dependent variable. To mitigate the risk of bias due to idiosyncratic errors, we estimate a population-averaged model for the first five years after VC investment.

Table 9: Estimated ATTs on economic size, by moderating variable.

	ln (Tot. assets) (1)	ln (Revenues) (2)	ln (Op. costs) (3)	ln (Staff costs) (4)
	OLS	OLS	OLS	OLS
Investment period:				
2007-08	2.1910***	1.0864*	2.7648***	2.4288***
	(0.476)	(0.424)	(0.416)	(0.425)
2009-11	2.4203***	1.4766**	3.1372***	1.4424*
	(0.410)	(0.546)	(0.539)	(0.582)
2012-14	2.0902***	0.4342	1.4770***	1.0460**
	(0.349)	(0.373)	(0.366)	(0.394)
Macro-sector:				
ICT	2.2849***	0.9603**	2.2093***	1.8800***
	(0.362)	(0.334)	(0.334)	(0.392)
Life sciences	1.8560***	-0.0739	1.7206**	1.0703*
	(0.353)	(0.538)	(0.524)	(0.455)
Services	2.7422***	0.8788	2.5422***	0.8959
	(0.563)	(0.790)	(0.704)	(0.785)
Other	1.7560**	1.7663**	2.7453***	1.9105*
	(0.629)	(0.619)	(0.795)	(0.781)
Innovativeness score:				
Below 30%	2.3935***	1.5224**	3.0079***	2.2714***
	(0.486)	(0.491)	(0.415)	(0.507)
Between 30% and 70%	3.5653***	1.4810	2.8324*	1.8006
	(0.835)	(0.922)	(1.240)	(1.499)
Above 70%	1.8764***	0.4089	1.6501***	1.1266***
	(0.236)	(0.303)	(0.320)	(0.294)
Age at investment:				
1 yr or below	2.3165***	0.5547	2.1650***	1.6073***
	(0.338)	(0.373)	(0.371)	(0.376)
2 to 5 yrs	1.8456***	0.9166*	2.0808***	1.3817***
	(0.325)	(0.366)	(0.361)	(0.395)
5 or more yrs	3.0659**	1.8598*	2.8155***	1.1921
	(0.946)	(0.722)	(0.810)	(0.771)
Macro-region:				
DACH	2.1649***	0.5373	0.9019	0.2423
	(0.303)	(0.413)	(0.905)	(0.619)
Nordics	0.3886	-0.4769	0.9459*	1.1213*
	(0.494)	(0.594)	(0.456)	(0.478)
France & Benelux	2.1438***	1.2898†	2.2518***	1.6979*
	(0.569)	(0.714)	(0.580)	(0.744)
South & CESEE	1.7752**	0.3196	1.9891**	0.4660
	(0.573)	(0.830)	(0.672)	(0.786)
UK & Ireland	2.7693***	1.8741***	3.1502***	2.4382***
	(0.387)	(0.398)	(0.353)	(0.388)
N° of observations	525	355	288	264
N° of firms	525	355	288	264
N° of treated	256	147	123	118
T-test on PS (p-value)	0.212	0.095	0.164	0.146

† 0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets;
Note: differences in point estimates do not necessarily imply statistically significant deviations across ATTs in sub-groups.

perceived innovativeness plays when young start-ups seek external financing: start-ups with highly perceived innovative capacity may find it relatively easier to obtain financing alternative to VC, as opposed to the least innovative category that therefore reaps the highest benefits from VC. In terms of age at investment, start-ups aged 5 or more years tend to benefit the most in terms of turnover. This finding is in line with the expectation that, by their 5th year of age, most start-ups will have a marketable product/service to fuel their sales.

The highest number of significant differences in the estimated ATTs emerges when comparing start-ups from different macro-regions.[33] While all but one point estimate for ATTs are positive, treatment effects in the UK and Ireland are significantly higher than in any other observed European region. Start-ups located in France and Benelux are a close second. The non-significant results for the effects across Nordic countries are due to the very low sample sizes (only about 30 treated firms analysed) and the presence of a couple of outliers in the control group, affecting the average estimates.[34]

Differences across macro-regions at least partially reflect the large heterogeneity in the European VC ecosystem, a topic we already explored in Kraemer-Eis *et al.* (2016) and Signore (2016). For this reason, the effects over macro-region may not be entirely comparable. For instance, the relatively lower magnitude of the ATTs in some regions may be explained by "thin" start-up markets, characterised by high selection and low survivorship, where (surviving) control firms represent more the "exception" than the norm. In such context, a potential outcome to benchmark VC-backed start-ups against would be the complete lack of funding, hence business initiative. This potential outcome is de facto excluded from our approach.

6 Robustness Checks

6.1 Robustness to model misspecification

The empirical approach discussed so far is not deprived of limitations, which we discuss here. We are mindful of omitted-variable bias (OVB) which could influence result estimates. Presence of unobserved effects might violate the unconfoundedness assumption, i.e. were features affecting treatment assignment not controlled for. An example of unobserved characteristics is the lack of more substantial information on start-up founders. To address these concerns, Appendix G discusses a battery of tests evaluating the robustness of our main results vis-à-vis model specification errors. We briefly summarise here the main insights from these additional analyses.

Our first robustness check involves the use of Rosenbaum's sensitivity analysis (Rosenbaum, 2005) to re-estimate our results, while artificially introducing different levels of hidden bias. Our findings suggest a relatively high bias insensitivity: treatment companies could be between 20% (turnover) to more than two times (assets, costs, pre-tax profit) more likely to obtain VC financing, before we witness a loss of significance in the associated baseline estimate. See Appendix G for detailed results.

Our second attempt at reducing OVB entails the addition of a measure of founders' connectedness in the start-up ecosystem. This measure combines network theory and information about entrepreneurs' prior founding experiences to derive a measure of network centrality, presumably affecting founders' access to VC and/or alternative financing. However, one major concern with this variable is its likely endogeneity, since we are not able to completely disentangle true founders from initial board members of start-ups (refer to the detailed discussion in section 4.2.2). As opposed to our prior founder-level variables, not likely to be affected by this measurement error, this variable might be capturing

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[33] Southern and Eastern Europe have been grouped together in this analysis due to the small final sample size. As such, results for this macro-region may not represent the situation in each underlying country.

[34] Inspecting the full distribution of outcome variables reveals a visibly positive treatment effect.

the endogenous centrality of VC investors that control board seats in their invested start-ups. Against this background, under the caveat of potential endogeneity, Appendix G shows that our baseline results are largely unaffected by the use of this additional predictor of VC financing.

An alternative approach to address OVB consists in the modelling of the unobserved effects. In general, the bias could stem from two types of unobservables — time-invariant and time-varying. The issue linked to the first type of unobservables could be solved by combining matching with a differences in differences (diff-in-diff) estimator (Ashenfelter, 1978) where the difference in the average outcomes in treated firms over time is subtracted from the average difference over time in control firms. This would strip away all companies of any time-invariant unobserved characteristics as well as biases resulting from time trends unrelated to the treatment. Such strategy could represent a more robust approach and would further confirm the causality of the estimated treatment effects.

However, since we analyse very young companies, starting their operations around the time of VC investment, they rarely have any financial history. In fact, one of our pre-conditions to qualify for early stage financing, as discussed in Appendix B, is that firms are pre-revenue. Therefore, we choose to implement the combined matching and diff-in-diff estimator only as a further robustness check, aware that this strategy will entail significant sample selection. We present the results of this additional analysis in Appendix G. The combined matching and diff-in-diff estimator generates point estimates that are in line with our baseline results. These show, however, typically lower magnitudes, as well as weak significance in some periods. While lower magnitude points to a certain degree of OVB in our baseline results, we should also note that the significant sample selection introduced by this approach does not allow for concluding evidence. Similarly, the lower significance levels are caused by the lower sample sizes, which considerably reduce the statistical power of our tests.

Overall, our robustness checks point to a possible upward bias in our baseline results. As shown by the Rosenbaum's sensitivity analysis this bias is, however, unlikely to affect the general indication of our causal analysis. That is, VC-backed start-ups experience a boost in short-to-medium term company growth that, in all likelihood, would have not otherwise happened.

Note that the combined matching and diff-in-diff estimator would still suffer from potential bias caused by unobserved time-varying effects. One such case is treatment anticipation — treated companies altering their behaviour to increase their chances of receiving VC financing. Should treated firms adjust any of the covariates affecting the assignment mechanism in anticipation of the treatment, such adjustments would be endogenous. In this instance, the estimated effects would only account for the part of the ATT that is not already captured by the endogenous changes.

Although treatment anticipation can be an issue in principle, we do not believe it to be a cause for much concern in our case. The observed firm characteristics used in our matching model, e.g. location, age, patent ownership are either costly or impossible to alter. Potentially omitted variables, e.g. founder education, are also typically very challenging to alter in such short time frame.

6.2 Representativeness of main results

Our data-intensive identification strategy provides desirable advantages in terms of causal inference and bias reduction. However, these come at the cost of data loss, hence potential sample selection.

This might affect the representativeness of our baseline estimates. To test the robustness of our results to more parsimonious matching strategies, Appendix H estimates the treatment effects by means of two alternative matching methods. The first only carries out an exact matching, i.e. matching based on $\mathbf{H}_j$. The second employs a combined exact- and propensity score-based nearest neighbour matching with replacement, but without the calliper option.

The alternative estimates remain qualitatively similar to our baseline results. However, we detect quantitative differences, in particular, the exact matching model yields results that are higher than the PSM model without calliper, which in turn produces higher results than our baseline estimates. The general trend shown in Appendix H is, therefore, that our baseline model is better equipped at removing selection bias from our causal estimates, therefore yielding lower ATTs. Moreover, the stricter nature of our baseline matching allows to achieve a more balanced sample compared to the alternative strategies.

Regardless of the matching approach, we are unable to use the entire population of EIF VC-backed start-ups in the ATT regressions, since not all firms could be matched with a control or have available financial data. In order to ensure the estimated effects are not the result of selection dynamics underlying this data unavailability issue, Appendix H addresses potential selection bias in data availability through a Heckman selection model (Heckman, 1979), assigning a weight to each treatment-control pair. Such weight is equivalent to the inverse Mills ratio stemming from a logit model estimating the likelihood of a given treated firm to be included in the final estimation sample. Our results remain strongly significant and numerically similar. This hints that our main results are rather well representative of the overall population of EIF-backed start-ups.

Motivated by the same goal, our last robustness check analyses potential difference in the treatment effects across the distribution of our various dependent variables. To this end, Appendix H employs quantile treatment effects analysis (Koenker and Bassett, 1978). Our results show no significant deviation across the three quartiles of the distribution for any outcome of interest, nor any differences between the quartile effects and the ATTs. We conclude that VC investments have a rather homogeneous effect over the distribution of the firm size indicators presented in section 5. This implies that, other than the moderating effects analysed in section 5.4, no additional subset of firms seems to experience significantly higher or lower treatment effects.

7 Conclusions

In this paper, we discuss and implement a quantitative approach to assess the economic impact of EIF-backed VC investments. Our work is based on a novel dataset aggregating information about all European start-ups supported by VC in the years 2007 to 2014, using data provided by Invest Europe, the European Private Equity and Venture Capital association. We augment this data with financial performance figures from Bureau Van Dijk's Orbis database.

Our empirical strategy is based on the estimator of Abadie and Imbens (2006), implemented through a combination of exact- and propensity score-based matching. Our matching model leverages on a set of standard as well as innovative measures that predict the exposure to VC financing. For instance, we use machine learning to predict the rate of innovation of start-ups. Our algorithm is trained to recognise highly innovative business models from short text descriptions. Moreover, we measure the "accessibility" of start-ups vis-à-vis active VC firms through network theory, modelling the European VC ecosystem as a network of VC hubs connected by flight routes. Finally, we use geospatial data to predict the volatility of local home equity markets, which in turn indicates the quality of collateral when entrepreneurs apply for financing, e.g. bank loans.

Our results document the positive effects of EIF-supported VC investments on start-up performance, as measured through various financial indicators (e.g. assets, revenue, employment). To summarise our findings, we give here an "investment lifecycle" perspective. The VC investment generates a temporary imbalance that tends to favour equity over liabilities. This translates into excess liquidity that start-ups use to fuel their scaling up process. As a result, we observe a rise in the financial "firepower" that start-ups use to acquire key production inputs, i.e. labour and capital. This propagates through the start-up's production function, positively affecting turnover levels for the treated.

In the medium run, both the equity and cash surpluses are replaced by an increased use of debt-type financing. VC-backed start-ups borrow significantly more than their counterfactuals, mostly to sustain their faster size growth. Given that this result is achieved through relatively lower shares of collateral in their balance sheet (e.g. tangible assets), we can conclude that VC helps start-ups secure further debt financing. In general, VC-backed start-ups adjust their mix of external financing, reducing their reliance on equity in the medium term.

The VC-induced size increase is often pursued by trading off profitability — although short-to-medium term financial losses are the norm for both evaluated groups. However, treated start-ups tend to catch-up with controls in the medium term. In addition, we find no evidence of obvious cost inefficiencies brought by the VC financing itself. VC investments simply enable treated firms to trade off higher levels of short-term profitability than they could have otherwise had, in exchange of faster growth.

We do not detect significant deviations in the effects that can be attributed to start-up characteristics, with the exception of the geographic macro-region, e.g. UK and Ireland, France and Benelux exhibit higher growth. However, effects across macro-regions are not entirely comparable, due to the large heterogeneity in the European VC ecosystem in terms of size and development of regional VC markets.

There are some limitations to our empirical approach. We discuss and address these in section 6. In general, we find our results robust to possible errors in the model specification as well as the matching strategy. Furthermore, the nature of our dataset only allows for a high-level analysis of financial accounts, reducing the number of observable start-up dynamics — for instance, R&D expenses, exports and the sources of external financing are not traceable.

Overall, our work provides meaningful evidence towards the positive effects of EIF-supported VC investment on the financial growth of young and innovative businesses in Europe. These findings, in line with the existing economic literature, point to the effectiveness of EIF's policy instruments supporting SME access to VC financing in Europe. Finally, we contribute to the literature by constructing a new dataset as well as multiple innovative metrics to predict the allocation of VC. Future research under this series, based on a similar approach, will analyse the effects of EIF-backed venture capital financing on investment outcomes and innovation.

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Appendices

A Sectoral classification

Table A1: Sectoral classification: concordance table

Macro-sector	Sector (full name)	Sector (short-hand)	Invest Europe sector	Nace Rev. 2 classes
ICT	Business related software	biz-software	34	6201
	Communication	communication	19; 20; 22; 21	1810; 1811; 1812; 1813; 1820; 2630; 4652; 4742; 5800; 5810; 5811; 5813; 5814; 5819; 5820; 5821; 5829; 5910; 5911; 5912; 5913; 5914; 5920; 6000; 6010; 6020; 6110; 6120; 6190; 6391; 6399; 7310; 7311; 7312; 9512
	Computer & electronics	pc-electronics	27; 29; 28; 30	2610; 2611; 2612; 2620; 2640; 2680; 4743
	Computer & data services	pc-data-services	40; 39	4651; 4741; 6202; 6203; 6209; 6310; 9511
	Internet technologies	internet-tech	25	6310; 6311; 6312
Life sciences	Biotechnology	biotech	60	7210; 7211; 7219
	Healthcare	healthcare	64; 65; 66; 62	2100; 2110; 2120; 2660; 3250; 3313; 4774; 8610; 8621; 8622; 8623; 8690; 8710; 8720; 8730; 8810; 8891; 8899
Services	Business & industrial services	biz-industrial-services	14	3311; 3312; 3314; 3315; 3316; 3317; 3319; 3320; 4661; 4662; 4664; 4666; 4669; 4674; 4690; 5210; 5221; 5222; 5223; 5224; 5229; 5320; 6900; 6910; 6920; 7010; 7020; 7021; 7022; 7110; 7111; 7112; 7120; 7320; 7410; 7420; 7430; 7490; 7710; 7711; 7712; 7721; 7722; 7729; 7730; 7732; 7733; 7739; 7740; 7810; 7820; 7830; 8010; 8020; 8110; 8121; 8122; 8130; 8200; 8210; 8211; 8219; 8220; 8230; 8290; 8291; 8292; 8299; 9412
	Consumer services: other	consumer-services	47; 46; 45; 48	5510; 5520; 5530; 5590; 5610; 5621; 5629; 5630; 7220; 7900; 7910; 7911; 7912; 7990; 8412; 8510; 8520; 8531; 8532; 8542; 8552; 8553; 8559; 8560; 9001; 9002; 9003; 9004; 9200; 9311; 9312; 9313; 9319; 9321; 9329; 9499; 9600; 9602; 9604; 9609
	Financial institutions and services	financial-inst	57	4610; 4612; 4613; 4614; 4615; 4616; 4617; 4618; 4619; 6400; 6419; 6420; 6430; 6490; 6491; 6492; 6499; 6512; 6610; 6611; 6612; 6619; 6622; 6629; 6630
	Real estate	real-estate	58	6800; 6810; 6820; 6831; 6832
Other	Agriculture & animal production	agriculture	3; 2; 1; 4	0111; 0113; 0126; 0130; 0147; 0149; 0160; 0161; 0162; 0163; 0164; 0210; 0321; 0322; 4622; 4623; 7500

Source: authors, based on Invest Europe's sectoral classification (link).

(Table A1 continued)

Macro-sector	Sector (full name)	Sector (short-hand)	Invest Europe sector	Nace Rev. 2 classes
	Business & industrial products	biz-industrial-products	12; 11; 13	1610; 1621; 1623; 1624; 1629; 1712; 1721; 1723; 1729; 2211; 2222; 2229; 2319; 2343; 2410; 2420; 2441; 2442; 2451; 2452; 2453; 2454; 2521; 2529; 2530; 2540; 2550; 2561; 2562; 2572; 2573; 2591; 2593; 2594; 2599; 2650; 2651; 2652; 2670; 2710; 2711; 2712; 2720; 2730; 2731; 2732; 2733; 2740; 2790; 2800; 2810; 2811; 2812; 2813; 2814; 2815; 2821; 2822; 2825; 2829; 2830; 2841; 2849; 2890; 2891; 2892; 2893; 2895; 2896; 2899; 3101
	Chemicals & materials	chemicals-materials	9; 8; 5; 6; 7	0893; 2000; 2010; 2012; 2013; 2014; 2015; 2016; 2017; 2020; 2030; 2041; 2042; 2051; 2052; 2053; 2059; 2221; 2312; 2314; 4675; 4676; 4773
	Construction	construction	15	0812; 2223; 2320; 2331; 2332; 2344; 2350; 2361; 2362; 2363; 2364; 2370; 2399; 2511; 2512; 4100; 4110; 4120; 4200; 4211; 4212; 4213; 4221; 4222; 4299; 4313; 4321; 4322; 4329; 4332; 4333; 4334; 4391; 4399; 4663; 4673; 4750; 4752
	Consumer goods & retail	consumer-goods	42; 44; 41	1011; 1013; 1020; 1032; 1039; 1041; 1051; 1052; 1061; 1070; 1071; 1073; 1082; 1083; 1084; 1085; 1086; 1089; 1092; 1101; 1102; 1105; 1107; 1300; 1310; 1320; 1330; 1390; 1391; 1392; 1395; 1396; 1399; 1410; 1413; 1419; 1431; 1439; 1511; 1512; 1520; 2219; 2341; 2342; 2349; 2369; 2751; 3102; 3109; 3212; 3213; 3220; 3230; 3240; 3299; 4631; 4632; 4633; 4634; 4636; 4637; 4638; 4639; 4640; 4641; 4642; 4643; 4644; 4645; 4646; 4647; 4648; 4649; 4711; 4719; 4721; 4722; 4723; 4724; 4725; 4729; 4751; 4753; 4754; 4759; 4761; 4764; 4765; 4771; 4772; 4775; 4776; 4777; 4778; 4779; 4781; 4782; 4791; 4799; 9522; 9529; 9600; 9601; 9603
	Energy & environment	energy-environment	51; 55; 50; 52; 53	0610; 0620; 0729; 0910; 1920; 3500; 3511; 3512; 3513; 3514; 3521; 3522; 3530; 3600; 3700; 3811; 3820; 3821; 3831; 3832; 3900; 4671; 4672; 4677; 4730
	Transport	transport	16; 17	2910; 2920; 2932; 3011; 3012; 3030; 3090; 3091; 3092; 3099; 4510; 4511; 4519; 4520; 4530; 4531; 4532; 4540; 4910; 4931; 4939; 4940; 4941; 4942; 4950; 5020; 5040; 5100; 5110

B Identification of seed and start-up companies

In this appendix, we list the assumptions used in the identification of early stage start-ups. A first assumption pertains to the start-up's age at first investment date:

Assumption 1. *Seed* and *start-up* investments reach firms operating for less than 10 years.

While assumption 1 may seem overly rigid with respect to very specific areas of venture capital financing,[35] it proves to be a widespread metric to identify VC-backed startups, for instance in Bertoni and Martí (2011) in the context of the VICO project, and more recently in the first European Startup Monitor (GSA, 2015). However, we consider assumption 1 not sufficient *per se* to discern early stage from later stage investments. We therefore include two additional assumptions:

Assumption 2. *Seed* and *start-up* investments target companies reporting no positive turnover in the 2 years preceding investment date.

Assumption 2 pertains to the general definition of seed and start-up investments. Although this may vary across different sources,[36] the relevant scientific literature converges towards the principle that seed and start-up investments, often grouped together in the "early stage" bracket, target companies that, in their most advanced state, *"are gearing up to produce, market, and sell their products"* (Leslie and Wells, 2000, p. 243). The cut-off moment seems thus to be the generation of the first commercial returns, for which our assumption aims at accounting for.

Finally, we impose a third assumption, this time aimed at invested companies' size:

Assumption 3. *Seed* and *start-up* investments target companies with less than 250 employees at investment date.

Many reports and studies show that 250 is already an unrealistic upper-bound for headcount levels in seed and start-up companies (see for instance Davila *et al.* 2003, p. 696). However, this relatively high threshold reflects the notion that start-up companies constitute a subset of the broader SME category, the overarching target group of EIF-managed programmes.

The joint verification of assumption 1 and one or both assumptions 2-3 classifies EIF-backed VC companies in our original dataset as "true" seed and start-up first-invested companies. For a small portion of our dataset, data availability issues prevent us from verifying assumption 2 or 3: in such cases, we follow the "benefit-of-the-doubt" approach and consider the underlying companies early stage start-ups.

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35 In particular in the life science category, where the gestation period before product commercialisation can occasionally overcome this arbitrary time limit.

36 For instance, Invest Europe definition of start-up financing excludes that targeted companies generate commercial return, while the definition adopted by the European Startup Monitor includes companies that already generate their first revenue.

C Identification of innovative business models via deep learning algorithms

The "innovativeness" of investment proposals is a key criterion used by VC firms to evaluate new ventures (Manigart *et al.*, 1997). According to Kollmann and Kuckertz (2010), who surveyed 81 European VC firms, most venture capitalists can confidently assess whether the investment proposals meet their requirements in terms of innovativeness. VC firms typically do so right at the start of the appraisal process. For this reason, investing in innovative companies is considered among the distinctive traits of venture capitalists (Bottazzi and Da Rin, 2002).

However, conceptualising the VC firm's drive towards innovative ventures proves a challenging task. First, the perceived innovativeness of business proposals can be highly subjective, particularly in the absence of signalling tools (e.g., patents). Second, there seems to be some disagreement among VC firms on the importance of innovativeness itself. For instance, in Macmillan *et al.* (1985b) a sizeable portion of respondent VC firms did not even consider innovativeness a key requirement for investment.

Intuitively, VC firms predict innovativeness by evaluating the strategy of the entrepreneur(s) to achieve their vision: we call this the "entrepreneurial orientation" (EO) of the start-up, borrowing the term from the strategic management literature. EO is composed of *"policies and practices that provide a basis for [new] entrepreneurial decisions and actions"*, allowing to fulfil the start-up's *"organizational purpose, sustain its vision, and create competitive advantage(s)"* (Rauch *et al.*, 2009, p.761).

High EO is linked to a high propensity towards the creation of new products, processes and services. It is also linked to high risk taking and competitive proactiveness (Hult *et al.*, 2004). Thus, we assume that VC firms evaluate the innovativeness of new venture proposals based on the *latent* continuous variable EO. We assume, however, that they can only observe one of two levels of EO: *high* or *low*.

We collect the trade description of a start-up — a short overview of its activity and strategy — and assume it consistently approximates its entrepreneurial orientation. Trade descriptions are compiled by Bureau Van Dijk, based on start-ups' websites and/or desktop search. While the *third-party* nature of these short texts improves homogeneity and mitigates the risk of finding over-emphasised EOs, a drawback of this proxy is that it is occasionally vague and/or outright inadequate for our evaluation.

How do VC firms assess the entrepreneurial orientation and the innovative capacity of start-ups? The empirical literature on this topic is rather thin (a noteworthy exception being Fried and Hisrich, 1994), so we rely instead on anecdotal evidence and heuristic techniques. For instance, VC firms often correlate high innovativeness with high risk, an aspect that they counter through higher hurdle rates, i.e. higher projected returns that a proposal must meet to be attractive (Baeyens *et al.*, 2006).

Based on this principle, we classify trade descriptions via two key markers: the risk/return profile and the trade's reliance on R&D. We favour trade descriptions that venture into *new* markets and industries, doing so via their willingness to develop new products, processes and services. This approach aligns well with Pavitt's taxonomy (Pavitt, 1984, 1990), our main point of reference. To ease our classification exercise, we further use a few *ad hoc* practical rules. For instance, we assign *low* innovativeness status to firms exclusively active in IT training, IT consultancy, online marketing: we consider these *traditional* business models that merely use IT as medium.[37] In addition, we assign *low* innovativeness to trade descriptions that are too vague to allow for proper evaluation, e.g. because they are not any more detailed than the main NACE Rev. 2 industry classification of the start-up.[38]

The classification exercise needs to be carried on 244,181 unique trade descriptions associated to 12,333 treated and 362,693 non-treated start-ups.[39] Moreover, about 75 percent of trade descriptions are written in a language other than English, requiring translation prior to being classified. We translate all foreign-spelled descriptions using the online translation engine offered by Yandex.

To prevent the sheer size of our sample be an obstacle to our endeavour, we revert to deep learning algorithms. Deep learning models are very effective tools to approximate highly dimensional non-linear functions of some given inputs (Goodfellow *et al.*, 2016). In our case, the inputs are short texts containing trade descriptions, while the output is a binary *high/low*. The *function* to approximate corresponds to the VC firm's assessment of the innovativeness level, as per the theory outlined above.

To construct our training and validation datasets, we manually classify sentences from about 7,000 trade descriptions out of 23,027 randomly sampled treated and untreated start-ups, i.e. 3% of all data.[40] We classified sentences — *bits* of trade descriptions instead of the full text — to reduce the "noise" in cases when only one passage among several clearly identifies the start-up as innovative.[41]

After testing several deep learning models, we opt for the residual Long Short-term Memory model (residual LSTM, He *et al.*, 2016). The Long Short-term Memory network (LSTM, Hochreiter and Schmidhuber, 1997) is a variation of the recurrent neural network (RNN, Elman, 1990), a neural network architecture that is particularly suited for sequence learning.

Intuitively, in a short text the meaning of a specific word can be influenced by both previous and subsequent words (e.g., "software development" *vs* "software installation" in the context of our exercise). As opposed to conventional neural networks,[42] RNNs update the weight assigned to each input in the sequence while keeping track of previous inputs. They do so through a *hidden state*, a high-dimensional matrix that stores the interim output of the model as it scans through the sequence. The hidden state acts as a "memory" that influences the final output of the network over subsequent iterations (Graves, 2012). The more hidden states, the more a model becomes "deep".[43]

RNNs are known to suffer from the *vanishing gradient problem*. This causes certain parameters of the network to grow or decay exponentially as the model converges, preventing the model from reaching

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37 Except for *online retail*, due to its transactional and logistical challenges *vis-à-vis* the offline retail industry.

38 An exception to this rule is the Biotechnology industry, which is always classified as highly innovative.

39 To improve our ability to classify the EO of start-ups, we carry out this exercise on all equity-supported companies from the EIF-Invest Europe combined set. See section 3 for our sample selection approach.

40 We originally sampled 5% of descriptions from an initial set of untreated start-ups. The initial set was later enlarged via re-samplings, due to the small sample sizes obtained in a few strata. Since all samplings were random, further extending the manual classification set was not deemed necessary.

41 In the training phase, we purge common English *stop words* and punctuation from sentences, and truncate each sentence to 25 words maximum (before truncation, 95% of sentences have 25 words or less).

42 The so-called feed-forward neural networks (see Goodfellow *et al.*, 2016).

43 As the number of hidden layers rises, the model yields a *hierarchy* of increasingly abstract interim outputs.

the optimal set of parameters. To address the issue, Hochreiter and Schmidhuber (1997) proposed the LSTM model, further refined in Gers *et al.* (1999) and Gers and Schmidhuber (2000). The LSTM architecture solves the *vanishing gradient problem* by allowing the model to "keep" in memory or "forget" certain previous inputs before their weights become subjected to exponential decay/growth.

However, much like RNNs, LSTMs remain rather difficult models to train, particularly as their depth increases. To address the trade-off between increased abstraction and ability to reach satisfactory convergence, He *et al.* (2016) proposed the residual LSTM. Instead of "stacking" hidden layers (i.e., using interim outputs of one layer as the inputs for the subsequent layer), the residual LSTM architecture uses such layers iteratively, to "carve out" residual knowledge about the outcome function. This way, each layer of a residual LSTM only learns about the information left unexplained by past layers.

Formally, let $\ell = 1 \dots L$ represent a given layer in the network architecture. Let also $\mathbf{x}_t \in \Re^d$ be a sequence of words in a short text, where d is the dimensionality of the numerical representation of a word and t is the *time step*, e.g. a word's position in the sequence. We define $\mathbf{h}_t^\ell \in \Re^n$ as the *hidden state* vector in layer ℓ at time step t. Let $\mathbf{h}_t^L$ be our prediction for the outcome $\mathbf{y}_t$, and $\mathbf{h}_t^0 = \mathbf{x}_t$.

The output $\mathbf{h}_t^\ell$ for layer ℓ and time step t is defined by the following set of equations:

$$\begin{cases} \mathbf{i}_t^\ell = \sigma\left(\mathbf{W}^{(i)}\mathbf{h}_t^{\ell-1} + \mathbf{U}^{(i)}\mathbf{h}_{t-1}^\ell + \mathbf{b}^{(i)}\right) \\ \mathbf{o}_t^\ell = \sigma\left(\mathbf{W}^{(o)}\mathbf{h}_t^{\ell-1} + \mathbf{U}^{(o)}\mathbf{h}_{t-1}^\ell + \mathbf{b}^{(o)}\right) \\ \mathbf{f}_t^\ell = \sigma\left(\mathbf{W}^{(f)}\mathbf{h}_t^{\ell-1} + \mathbf{U}^{(f)}\mathbf{h}_{t-1}^\ell + \mathbf{b}^{(f)}\right) \\ \mathbf{c}_t^\ell = \mathbf{i}_t^\ell \odot \tanh\left(\mathbf{W}^{(c)}\mathbf{h}_t^{\ell-1} + \mathbf{U}^{(c)}\mathbf{h}_{t-1}^\ell + \mathbf{b}^{(c)}\right) + \mathbf{f}_t^\ell \odot \mathbf{c}_{t-1}^\ell \\ \mathbf{h}_t^\ell = \mathbf{o}_t^\ell \odot \left(\tanh\left(\mathbf{c}_t^\ell\right) + \mathbf{h}_t^{\ell-1}\right) \end{cases}$$

where σ and $\tanh$ are, respectively, the logistic and the hyperbolic tangent element-wise functions transforming values to the range $[0, 1]$. The terms $\mathbf{W}^{(\cdot)} \in \Re^{\ell \times d}$ and $\mathbf{U}^{(\cdot)} \in \Re^{\ell \times \ell}$ are the tensors containing the weights of the network that we wish to train, while $\mathbf{b}^{(\cdot)} \in \Re^\ell$ is a tensor of trainable constant terms (called *biases*). The term $\mathbf{c}_t^\ell$ is the *memory cell*, a central element of the LSTM architecture, which prevents the issue of the vanishing/exploding gradient (Hochreiter and Schmidhuber, 1997). The terms $\mathbf{i}_t^\ell, \mathbf{o}_t^\ell, \mathbf{f}_t^\ell$ are called respectively the *input*, *output* and *forget* gate.

Before fitting the residual LSTM model, we must select a suitable word embedding technique. This determines the way each word in the *corpus* of short trade descriptions is represented numerically in our deep learning model. For instance, each word could be indexed to a number (an approach called "one-hot" encoding). However, such approach would be sub-optimal, as it does not capture the similarity between words (e.g., school *vs* education).

Our final choice is to employ fastText, a pre-trained continuous word representation.[44] fastText is yet another neural network trained on very large text corpora (e.g., Wikipedia, news articles, online blogs). A key feature of fastText is that its resulting word vectors achieve semantic properties, i.e. synonyms tend to have similar vector representations while antonyms fall far apart in the vector space.

[44] See Bojanowski *et al.* (2017) and Mikolov *et al.* (2017) for technical details.

Word analogies become possible as well.[45] This provides significant performance advantages when models are trained on limited amount of data, e.g. the rather small dictionary of 7,465 words in our training data. Overall, fastText played a key role in the high performance of our classification task.

Our final model contains 5 hidden LSTM layers with 300, 120, 120, 60 and 60 hidden nodes respectively.[46] Table C1 shows some key performance metrics for our final model against similar and/or comparable architectures. Among the different tested architectures, the residual LSTM architecture performs best in terms of area under the receiver operating characteristic (ROC) curve, also generating the lowest amount of validation loss observed (see also Figure C1). In addition, the residual LSTM provides a low and balanced rate of type I (false positives) and type II (false negatives) errors, in contrast with other architectures which mostly focus on minimising the false positive rate.

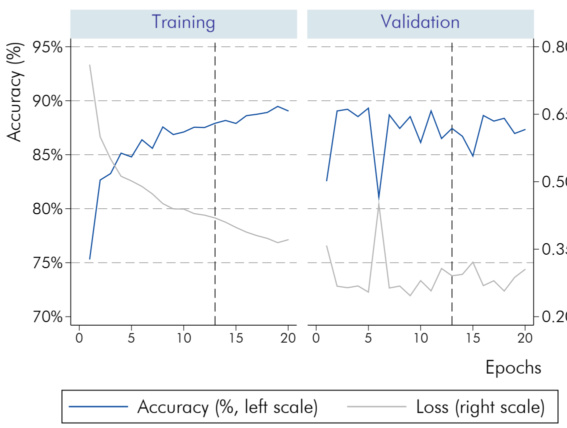
Table C1: Performance comparison of different deep learning architectures

Model name	Architecture	Training epochs	Hidden layers	Validation accuracy	Validation loss	Area under the ROC curve	False positive rate	False negative rate
Final model (FM)	resLSTM	13	5	0.871	0.304	95.27%	13.55%	10.48%
FM, over-trained	resLSTM	20	5	0.873	0.305	94.94%	13.03%	11.25%
Stacked LSTM	LSTM	13	5	0.906	0.324	93.75%	8.31%	13.55%
Bidiretional LSTM	biLSTM[a]	13	3	0.903	0.409	93.56%	6.94%	20.46%
Convolutional NN	CNN[b]	13	2	0.905	0.474	94.42%	6.67%	20.46%

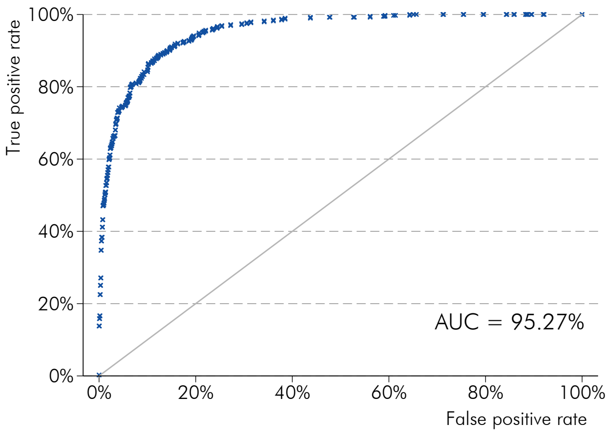
[a] Graves *et al.* (2013) [b] LeCun *et al.* (1999)

The left side of Figure C1 displays the training and validation progress of the final classification model. The erratic behaviour of the validation progress curve is explained by high *dropout* rates. The dropout technique (Srivastava *et al.*, 2014), by blocking the convergence of a random set of nodes at each step, significantly improves the ability of our model to perform out-of-sample predictions.

Figure C1: Convergence and performance of final residual LSTM model



(a) Training and validation progress



(b) Receiver operating characteristic curve

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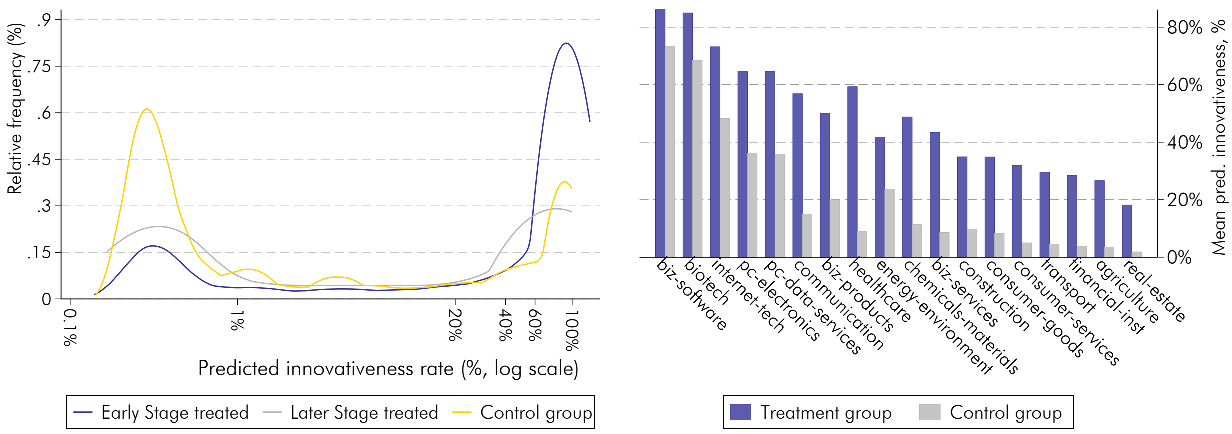
45 E.g., the word embedding operation "Berlin − Germany + France" yields a vector very close to the one of the word "Paris". Similarly, "King − Man + Woman" yields approximately "Queen".

46 We use linear activation layers to scale each intermediate output to the number of inputs required by the next layer. We also stack on top of our network a rectified linear unit and a final logistic activation layer.

We now turn to some empirical regularities that support the validity of our predicted rate of innovativeness. In the left side of Figure C2, we plot the distribution of the predicted scores for each evaluation group. Compared to start-ups from the same countries, sectors and age cohorts, VC-backed companies tend to have higher innovativeness, a signal of its important role in the decision-making process of VC firms.[47] At the same time, the sizable share of treated start-ups with low innovativeness hints that this is not *per se* a precondition to VC investment, but other factors also come into play. In particular, we note that the presence of prior measurable financial performance — typically the case for later stage investments — reduces the importance of high innovativeness in start-up investing.

Figure C2: Distributional features of the predicted innovativeness rate



(a) Innovativeness distribution by evaluation group (b) Average innovativeness by aggregate sector

The right side of Figure C2 plots the average predicted innovativeness by evaluation group and industry.[48] In line with our expectations, sectors such as biotechnologies, internet technologies and business software tend to have the highest average innovativeness. On the opposite end, we find real estate, agriculture, transport and financial instruments.[49] Interestingly, the gap in innovativeness between treated and untreated start-ups tends to widen as we move towards less innovative sectors.

Concluding our series of diagnostics, Table C2 provides a randomly extracted sample of trade descriptions and their related predicted score. All scores are the result of out-of-sample predictions by our deep learning model. Trade descriptions are ranked by quintile of innovativeness (from lowest to highest), showing the implied scale of innovativeness resulting from our training data. A visual inspection of Table C2 highlights a series of keywords that "persuade" the deep learning model to assign high innovativeness. In line with intuition, *design*, *development*, but also *research* tend to be positive markers for high innovativeness.[50]

47 Note that the manual classification was *blind*, *i.e.* the evaluation group and start-up identity were not known during the exercise, lowering the chances of artificially inflated innovativeness for treated start-ups.

48 For the full denomination of our aggregate industries, refer to Appendix A.

49 Despite the emergence of the *FinTech* industry — clearly over-represented in the treatment group — the whole financial sector is typically characterised by high organisation and/or marketing innovation and relatively low product and/or process innovation, see *e.g.* Eurostat's Community Innovation Survey (CIS).

50 This is possibly the reason why the trade description "Physiotherapy services..." receives a rather high innovativeness score of 26.07%, perhaps more than should be deserved.

Table C2: Examples of trade descriptions and predicted innovativeness

Quintile of innovativeness	Pred. innovativeness score	Trade description text
1st	0.20 %	Engaged in the manufacture and sale of printable T-shirts, sweatshirts, polos, and other casual wear.
	0.25 %	Crushing of concrete and stone.
	0.27 %	Vehicle damage assessment for insurers.
2nd	25.00 %	The company's business shall be to engage in internet marketing.
	26.07 %	Physiotherapy services, training, lecturing and consulting. **Rehabilitation equipment rental, sales as well as product development and manufacturing.** Industry product sales. Rental business. For its operation, the company can own and manage immovable property, shares and the value of the shares.
	29.77 %	The supply of raw materials for the production of agrochemicals, veterinary products and resins for the production of paint.
3rd	46.04 %	Installation and exploitation of a cyber-hub, that is to say, a local computers *(sic)* with connections to the internet, the public can use to exchange for a price.
	51.24 %	Engaged in the operation of a medical laboratory.
	56.68 %	The operation of a service company for electronics manufacturing, in particular for the protective coating of printed circuit boards (protection, coating and potting of electronic assemblies).
4th	63.73 %	Engaged in the production and distribution of advanced composites, carbon fiber, and structural film adhesives.
	69.33 %	Production and sale of nano-scale liquid - chromatography kolomnen† *(sic)* and electrospray emittors.
	79.06 %	Information technology services-coding, server maintenance.
5th	83.60 %	Engaged in the design, production and installation of standardized and special-purpose machines for machining processes involved in the production of automotive powertrains.
	98.37 %	Online mortgages and insurance comparison website operator.
	98.67 %	The design, development, manufacture and marketing of medical devices or reagents for use in vitro diagnostics or research.

Note: Words colored in **blue** are those fed to the deep learning model. The rest is excluded either in the pre-cleaning phase, or because fastText does not provide a vector representation for the specific word. The sentence in **bold** is the passage that assigns the score to the entire trade description. †Dutch term for "columns", left untranslated by the Yandex service.

Overall, we consider the classification performance of our deep learning tool satisfactory. However, we find it challenging to observe meaningful differences among descriptions scoring in the neighbourhood of 50% predicted innovativeness (*e.g.* 45% *vs* 65%). For this reason, when matching on this variable, we allow for wider matching intervals according to how close the predicted score is to 50%, *i.e.* complete uncertainty. See section 4.3 for details.

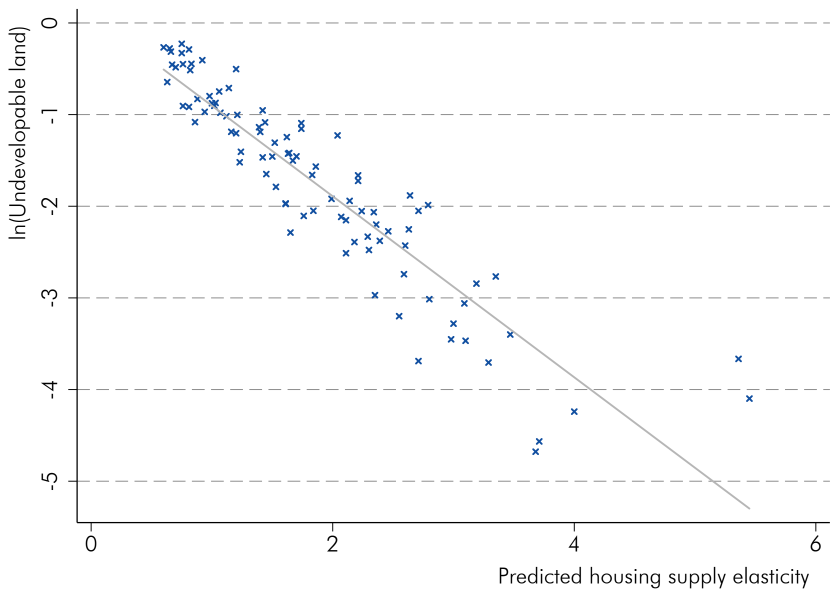
D Imputing housing supply elasticity via geographic information system methods

This appendix details the approach used to control for potential demand of venture capital in our propensity score model. Our objective is to identify exogenous sources of variation in the access to finance other than VC. In turn, this will allow to control for the willingness of entrepreneurs to look for VC financing. To this end, we follow the approach and rationale of Robb and Robinson (2014). In their paper, the authors employ housing prices as a potential exogenous factor to the value of collateral when entrepreneurs apply for bank credit.

Robb and Robinson argue that in markets where supply is perfectly inelastic, housing demand shocks translate directly into price shocks. This renders the value of home equity highly sensitive to changes in housing demand, therefore a poor form of collateral to pledge against bank loans. Conversely, the collateral value of entrepreneurs located in areas with highly elastic housing supply is less likely to be affected by aggregate housing demand. To test this identifying assumption, the authors use a predictor of housing supply elasticity developed by Saiz (2010). The measure is constructed by processing satellite-generated data with geographic information system (GIS) techniques, deriving the share of developable land within 50-kilometer radii from metropolitan central cities. Saiz claims that the share measures the *"exogenously undevelopable land in cities"* (Saiz, 2010, p.1254).

Saiz (2010) combines the GIS-based measure with an indicator for zoning restrictions (Gyourko *et al.*, 2008) to predict housing supply elasticity from a conventional urban economic model. Zoning restrictions are a common land use regulation tool in the US, albeit less popular in Europe (see Hirt, 2012). The author reports the share of undevelopable land and housing supply elasticity for 95 metropolitan statistical areas (MSA) in the US. Figure D3 illustrates the quasi-linear relationship between these two key variables.

Figure D3: Supply elasticity estimates and $\ln$ (undevelopable land) in Saiz (2010)



Source: Authors, based on Saiz (2010)

In the remainder, we detail our replication of Saiz's approach to estimate the share of undevelopable land for the European case. We choose functional urban areas (FUA) as our main geographical unit. The concept of FUA, developed in OECD (2012) and further refined by the European Commission and OECD,[51] is most similar to the MSA in the US. FUAs are identified from population grids and are composed by densely populated areas and their neighbouring commuting zones. We identify 687 FUAs located in 30 European countries (EU28, Norway and Switzerland), drawing circles of 40 km radius from each of their centroid.[52] The shorter radius is justified by the typically higher population densities we find in European cities.[53] This constitutes our initial amount of "*developable land*".

We first calculate the share of developable land lost to the sea using the European Environment Agency (EEA) coastline dataset.[54] We further subtract the share of land with slope above 15% (in line with Saiz, 2010), which is generally considered unsuitable for residential construction. We generate slope maps using the EU digital elevation model (EU-DEM) developed by the Copernicus Land Monitoring Service of the European Commission.[55] Finally, we substract the share of land lost to water bodies using the Copernicus Water and Wetness high resolution layer.[56] We considered all land covered by temporary/permanent water or wetness not suitable for construction. All layers employed in the analysis have a pixel resolution of 25 meters or below.

Table D3: Functional Urban Areas (FUAs) by share of undevelopable land (top and bottom 10)

Functional Urban Area	Undevelopable land (%)
Valletta, MT	95.52948
Thanet, UK	79.07122
Messina, IT	63.42009
Melilla, ES	62.95040
Cherbourg, FR	59.11571
Great Yarmouth, UK	59.03460
Ceuta, ES	58.56501
Reggio di Calabria, IT	57.28986
Middelburg, NL	57.25204
Siracusa, IT	56.95813
...	...
Koblenz, DE	0.22809
Plock, PL	0.22595
Hradec Králové, CZ	0.16452
Jastrzebie-Zdrój, PL	0.13054
Tübingen, DE	0.10102
Rybnik, PL	0.09868
Charleroi, BE	0.05481
Lódz, PL	0.01037
Bielsko-Biala, PL	0.00399
Kraków, PL	0.00006

As we lack complete time series on house prices for most European FUAs, we are not able to fully replicate Saiz's work and estimate the housing supply elasticities. We also lack an indicator of land use regulation, although as mentioned above the widespread use of "mixed-zoning" in Europe lowers this factor's ability to predict housing supply compared to the US. For these reasons, we use our GIS variable as a proxy for housing supply elasticity, also given their quasi-linear relationship (Figure D3).

[51] See European cities – the EU-OECD functional urban area definition.

[52] In fact, the average radius is 42.78 km, due to one inaccuracy in the GIS projection. This yields some variation based on the latitude of the FUAs. However, as the standard deviation for FUAs within a given country is lower than 1km, our final results are not affected by the inaccuracy.

[53] For instance, the median (mean) number of people per km^2 for MSAs in the US is 76.53 (116.82), while it is 204.24 (419.66) for FUAs in Europe (sources: Eurostat and U.S. Census Bureau).

[54] www.eea.europa.eu/data-and-maps/data/eea-coastline-for-analysis-1. Last accessed: June 2018.

[55] land.copernicus.eu. Last accessed: June 2018.

[56] land.copernicus.eu/pan-european/high-resolution-layers/water-wetness. Last accessed: June 2018.

E Network centrality measures for start-up accessibility using flight routes

This appendix details the construction of our index of geographic "accessibility" for treated and untreated start-ups, used as a proxy for the supply of venture capital. Lerner (1995) studies a sample of 271 biotechnology firms in the US receiving VC investments during 1978 and 1989, observing that geographic proximity is a key determinant of venture board membership. Bernstein *et al.* (2015) surveyed 306 VC investors, mostly US-based, finding that 9 out of 10 would increase their on-site involvement with a distant investee should a direct flight route be made available to them. Kraemer-Eis *et al.* (2016) also show how European VC firms tend to privilege short- and medium-distance investments. The concept of "accessibility" we employ in this work is inspired by these stylised facts.

Network theory provides a suitable framework to measure the "accessibility" — called *centrality* — of a given start-up with respect to the population of active VC firms. Network analysis treats the actors of a given ecosystem as *nodes*, and the connections among nodes as *edges*. The system can then be represented mathematically and appropriate statistical techniques can determine the importance of a given node/actor against all other nodes. A key role in our network is played by airports and flight routes, which are not new to this type of representation (*e.g.* Burghouwt *et al.*, 2003).

We obtained flight routes data from OpenFlights. We collected seven snapshots of the raw database in the years 2009 to 2017.[57] Over the analysed period, the database contains a total of 25,551 flight routes to and from 525 airports located in 30 European countries (EU28, Norway and Switzerland). A total of 14,294 airport-pairs form the backbone of our network. While we cannot thoroughly assess the representativeness of this data, we note that it compares rather well with alternative commercial providers of flight routes data (see *e.g.* Dobruszkes *et al.*, 2017).

Our analysis focuses on hubs instead of airports. We employ the notion of functional urban areas (FUAs), *i.e.* densely populated urban areas and their neighbouring commuting zones, which makes our indicator consistent with the measure "share of developable land" described in Appendix D. We assume that each FUA is reachable via all airports located no farther than 120km from its centroid.[58] This implies that a given airport may serve multiple FUAs. The final network contains 838 nodes and up to 297,350 edges.[59] The average number of routes between two hubs is 5.47 (the median is 4).

Our network should also incorporate information about the potential supply of venture capital. To this end, we gather information about the office location of European VC firms undertaking early and later stage investments. We retrieve this information from the 2017 version of Invest Europe's member directory,[60] complemented with data scraped from the websites of VC firms. Overall, we track more than 480 addresses of VC firms located in 78 FUAs, including the indicative time at which their business opened. While we cannot claim that our data is complete, we believe Invest Europe's member directory to be rather representative *vis-à-vis* the population of Europe-based VC firms.

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57 No available data existed prior to 2009, so our 2009 snapshot is assumed equivalent to the one in 2007.

58 We chose the arbitrary cut-off point by assuming that most business travellers would be willing to travel at most 2.5 hours at a 50km/h average speed in order to reach their departure airport. Wilken *et al.* (2005) calculate that a radius of 75km around German airports covers, on average, 72% of their traffic volume.

59 Note that 122 nodes relate to airports located at more than 120km distance from their nearest FUA.

60 https://www.investeurope.eu/about-us/members/directory. Last accessed: 2017-06-30.

The location of European VC firms, hence the potential supply of venture capital investments, allows us to weigh the edges in our network of FUAs in a way that privileges meaningful links. Intuitively, the chance of obtaining VC financing from a given location is zero if said location does not host any VC firm, and higher than zero otherwise. Similarly, the chances to receive investments from unconnected areas are significantly lower compared to areas served by numerous flight routes. Finally, physical distance remains a determining factor, with distant areas less likely to be served by a given VC firm.

Following this line of reasoning, we mirror the approach in Hossain *et al.* (2013) and assign a weight to each network edge, $\Delta_{k,m}$, defining the "distance" between source FUA k and destination FUA m:

$$\Delta_{k,m} = \begin{cases} \frac{d_{k,m}}{f_k \cdot r_{k,m}} & \text{if} \quad f_k > 0, r_{k,m} > 0 \\ \infty & \text{otherwise} \end{cases} \tag{1}$$

where $d_{k,m}$ is the geodetic distance between FUA k and m, f_k the number of investors in the source FUA and $r_{k,m}$ the number of connecting flight routes. All things equal, if either the number of investors in k or the number of routes between k and m increases, then FUA m will be "closer" to k and start-ups in m more likely to receive investments from VC firms located in k.[61]

After estimating various centrality measures for our network of functional urban areas,[62] we selected the PageRank centrality index (Page *et al.*, 1998) as a proxy for the "accessibility" of FUAs. The PageRank centrality index corresponds to the probability that a VC firm lands on a given FUA if it were to move randomly across our network of FUAs for an amount of time tending to infinity. This implies that the "quality" of connections also plays a role in determining a FUA's PageRank centrality: connections to central areas will be more valuable than those towards peripheral nodes.[63] This property aligns well with our notion of "accessibility": areas well connected to important VC hubs (*e.g.* London, Paris) are likely to experience a relative advantage in terms of access to VC financing.

To construct our accessibility index, we could assign to each start-up j the value ρ_{k^*}, *i.e.* the PageRank index from its closest FUA k^*. However, this would generate a biased representation should two start-ups be linked to the same closest FUA despite vastly different lengths. If distance plays a role, then it is also reasonable to assume that the distance between start-up's j and the "access point" of FUA k^* will be factored in by the VC firm. The "access point" of FUA k^* is defined as the *center of gravity* of the polygon determined by all neighbouring airports (weighted by the number of flight routes). For this reason, we discount from ρ_{k^*} the distance between start-up j's headquarters and FUA k^*'s access point to derive our final accessibility index α_j:

$$\alpha_j = \sqrt{\rho_{k^*}} \cdot e^{-\frac{\sigma_{jk}}{c}} \tag{2}$$

i.e. start-up j's accessibility is a function of FUA k^*'s PageRank centrality[64] and σ_{jk^*}, the distance between j and k^*'s access point. We assume $c = 50$ to be a normalizing constant.[65]

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[61] Note that $\Delta_{k,m}$ may differ from $\Delta_{m,k}$: for this reason, our network is a so-called "directed" graph.

[62] See Brandes and Erlebach (2005) for an overview of network centrality measures.

[63] To avoid exponential growth, we use a *dampening* factor $\alpha = 0.9$, in line with the literature.

[64] We use the square root of ρ_{k^*} to mitigate the skewness in the distribution of PageRank centralities.

[65] The constant is in line with an assumed average speed of 50km/h. See also footnote 58.

F List of financial indicators

Financial Indicator	Indicator dimension	Description	Formula
Capital	Size	Issued share capital (authorised capital)	
Total assets	Size	Total value of assets owned by the start-up	
Revenues	Size	Total operating revenues (incl. net sales, other operating revenues and stock variations); values do not include VAT	
Operating costs	Size	All costs related to the production of goods sold as well as commercial costs, administrative expenses, etc. plus depreciation of those costs	
Staff costs	Size	Detail of all the employees costs of the company (including pension costs)	
Cash	Asset allocation	The amount of cash at bank and in hand of the start-up	
Quick Ratio	Asset allocation	A measure of how well can the start-up meet its short-term financial liabilities	$QR = \frac{\text{Current assets - Stocks}}{\text{Current liabilities}}$
Tangible assets	Asset allocation	All tangible assets such as buildings, machinery, etc.	
Intangible assets	Asset allocation	All intangible assets such as formation expenses, research expenses, goodwill, development expenses and all other expenses with a long term effect	
Equity	Financing mix	Total equity (capital plus other shareholders funds)	
Total liabilities	Financing mix	Non current liabilities plus current liabilities	
Current liabilities	Financing mix	Current liabilities of the company (loans, creditors and other current liabilities)	
Other current liabilities	Financing mix	Other current liabilities such as pension, personnel costs, taxes, intragroup debts, accounts received in advance, etc.	
Non-current liabilities	Financing mix	Long term liabilities of the start-up (long term financial debts plus other long term liabilities and provisions)	
Profit/Loss before taxes	Profitability	Results from the aggregation of all operating and financial revenues minus all operating and financial expenses	
Return on assets	Profitability	An indicator of how profitable a company is relative to its total assets	$ROA = \frac{\text{Profit before tax}}{\text{Total assets}}$
Return on equity	Profitability	An indicator of how profitable a company is relative to its total equity	$ROE = \frac{\text{Profit/Loss before tax}}{\text{Total equity}}$

Source: Orbis, authors

G Robustness to model misspecification

Rosenbaum sensitivity analysis

Despite the rigorous matching procedure applied to identify the counterfactual group, there is still some uncertainty with respect to differences in the treatment and control companies. While in randomised control trials the comparability of the two groups is guaranteed by the random allocation, in observational studies it is impossible to test the fundamental unconfoundedness assumption. Therefore, it could be that the estimated results are caused by initial unobserved dissimilarities. Important covariates could be left unmeasured and, hence, unaccounted for by the matching algorithm.

This issue could be addressed with sensitivity analysis by estimating the level of unobserved covariates which still allows for significant treatment effects. By varying the extent of hidden bias, Γ, we can verify the level which qualitatively invalidates the analysis results. For each fixed level of Γ, the sensitivity analysis estimates bounds on the results, such as *P* values or confidence intervals. The degree of Γ at which results become insignificant is a measure of sensitivity to hidden bias (Rosenbaum, 2005).

Table G1 demonstrates Rosenbaum's sensitivity analysis for the dependent variables used in the regressions in section 5. More specifically, it shows the degree of hidden bias Γ at which differences are still valid at the conventional 5% significance level.

The sensitivity analysis results vary but overall they reveal robustness to hidden biases. Treatment effects on revenues represent the least robust result. The observed significant differences would be cancelled out if treatment companies had 20% or higher likelihood of receiving VC investments compared to the counterfactuals, e.g. due to unobserved characteristics. Conversely, ATTs on pre-tax profits demonstrate the most robust result: even if the matching had failed to control for unobserved characteristics strongly related to obtaining VC financing, thus rendering invested firms two and a half times more likely to receive it, this would still not explain away the significant treatment effects.

Table G1: Rosenbaum Sensitivity Analysis

Outcome variable	Γ (P-value $<$ 0.05)
ln(Capital)	1.7
ln(Total assets)	2.2
ln(Revenues)	1.2
ln(Op. costs)	2.2
ln(Staff costs)	1.5
ln(Long-term debt)	2.0
ln(Current liabilities)	1.6
ln(Pre-tax profit)	2.5

Robustness to model misspecification: the case of founders' reputation

In this robustness analysis, we introduce one additional variable to our propensity score model. This variable attempts at capturing the "connectedness", hence reputation, of founders within the wider entrepreneurial community. Social ties can play a crucial role in accessing finance, including VC (Shane and Cable, 2002). To approximate the effect of founders' social ties, we use network theory to calculate the centrality of entrepreneurs in a network composed of current founders and co-founders, as well as previous co-founders. As discussed in Appendix E, network theory is well suited to track the connectedness and centrality of agents in an economic system.

Starting from our exactly matched dataset containing treated and control start-ups (see section 4.3), we focus on the 140,055 management team members identified as likely founders (14,949 for treated firms, see section 4.2.2 for the approach). Entrepreneurs with previous founding experiences might tap into their existing network of business contacts to maximise their chances to obtain financing. Against this backdrop, we further concentrate on the 54,992 founders with past founding experience (7,921 VC-backed) and track co-founders linked to their prior entrepreneurial efforts.

The final network contains 1,442,912 founders, either directly involved in establishing treated or control firms, or connected to them through previous founding experiences. A "link" between two given members of this network represents a shared founding experience, i.e. one or more start-ups in which both are currently active (or were in the past). We identify a total of 6,960,542 links established in the period 2004 to 2013. To avoid the inclusion of founders' social ties that only materialise after treatment, we build year-specific networks, focusing only on existing ties before each respective year.

We compute the connectedness of a given founder by means of the network-theoretic index of "closeness centrality" (Bavelas, 1950). The index measures the reciprocal of the average distance of a given node from all other nodes, which suits our need to determine how well-rooted are founders within the wider entrepreneurial community. To overcome the computational challenges brought by the size of our network, we employ the technique in Cohen *et al.* (2014) to approximate the closeness index of each founder. Finally, we add this measure to our set of founder-level characteristics, re-estimate the propensity score model, and re-construct our final matching estimator (see section 4.3 for details).

In line with theory, Table G2 shows that the measure positively and significantly affects treatment assignment. However, the large magnitude of the odds ratio flags potential endogeneity (refer to the discussion in section 6). Table G3 proves that our alternative matching estimator fulfils the necessary balancing properties. Lastly, Table G4 shows the estimated ATTs from this alternative estimator. While our main results are maintained, the introduction of this variable causes a reduction in the magnitude of the ATTs on capital and costs, signalling its capacity to remove residual selection bias. Interestingly, the ATTs on the other economic size indicators are either unaffected or increase.

Table G2: Propensity score matching multi-level model. Dependent variable is treatment status.

	$\Pr(\text{treatment} = 1)$
	MULTI-LEVEL MIXED EFFECTS LOGIT
(output omitted)	
Founder's network closeness‡	26.6060***
	(13.442)
Log-likelihood	-6,332.24
Obs.	31,405
Pseudo-R^2 (McKelvey and Zavoina, 1975)	0.42
Area under the ROC curve	0.862

† 0.10 * 0.05 ** 0.01 *** 0.001; ‡ Founder-level characteristic; Exponentiated coefficients (odds-ratios).

Table G3: Descriptive statistics of PSM model and balancing checks

	Obs.		Mean		Median		St. dev.		P-value
	T	C	T	C	T	C	T	C	T/C
(output omitted)									
Founder's closeness index	272	272	0.44	0.43	0.45	0.38	0.419	0.434	0.762

Table G4: Estimated ATTs on economic size, by post-treatment period (augmented PSM model).

	ln (Capital) (1)	ln (Tot. assets) (2)	ln (Revenues) (3)	ln (Op. costs) (4)	ln (Staff costs) (5)
$ATT_{t=0}$	1.3095***	2.5667***	-0.9421**	0.9676***	1.1124***
	(0.289)	(0.274)	(0.331)	(0.258)	(0.324)
$ATT_{t=1}$	1.3227***	2.1216***	-0.0517	1.2791***	0.9503**
	(0.284)	(0.254)	(0.303)	(0.282)	(0.321)
$ATT_{t=2}$	1.3216***	2.1616***	0.8709**	1.7607***	1.6185***
	(0.308)	(0.249)	(0.320)	(0.321)	(0.295)
$ATT_{t=3}$	1.6623***	1.9067***	0.7212†	1.5171***	1.0290**
	(0.350)	(0.293)	(0.385)	(0.345)	(0.392)
$ATT_{t=4}$	1.8158***	2.2306***	0.9572*	1.8834***	1.1574**
	(0.426)	(0.324)	(0.405)	(0.435)	(0.365)
$ATT_{t=5}$	1.9551***	2.0802***	1.2101*	2.8088***	1.3130*
	(0.499)	(0.400)	(0.504)	(0.666)	(0.581)
N° of observations	2,266	2,313	1,213	1,008	881
N° of firms	495	502	356	286	255
N° of treated	243	246	150	123	118
T-test on PS (p-value)	0.284	0.275	0.131	0.181	0.247

† 0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets.

Modelling unobserved heterogeneity: diff-in-diff estimation

In this section we combine matching with diff-in-diff estimation (Bertrand *et al.*, 2004). This exercise seeks to test the robustness of our main results against the presence of time-invariant unobservables. The diff-in-diff estimator subtracts the average outcome of control firms from the mean outcome of treated, further deducting from the latter the difference in pre-treatment outcome levels. As a consequence, we do not analyse the effects of revenues here, since being pre-revenue is one of our prerequisites to fit into the early stage classification (see Appendix B). Table G5 shows the estimated ATTs for our main economic size indicators at the reference period $t = 3$.

Table G5: Estimated average treatment effects on the treated (diff-in-diff).

	ln (Capital) (1)	ln (Tot. assets) (2)	ln (Op. costs) (3)	ln (Staff costs) (4)
$ATT_{t=3}$	1.3229†	1.3371*	-0.2023	0.4940
	(0.677)	(0.612)	(0.681)	(0.798)
Obs.	296	306	78	70
Firms	148	153	39	35
Treated	73	73	19	16
T-test on PS (p-value)	0.019	0.055	0.044	0.001

† 0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets.

The insights provided by Table G5 are twofold. On the one hand, point estimates for the ATTs using the combined matching and difference-in-differences estimators are qualitatively similar to our baseline results. On the other hand, the significantly reduced sample sizes likely affect the statistical power of our test, i.e. our ability to detect significant effects, as well as the comparability of these results vis-à-vis our baseline estimates. In the case of operating and staff costs — columns (3) and (4) in Table G5 — estimates are based on less than 3% of the treated population, therefore hardly reliable.

H Representativeness of main results

Alternative matching strategies

We construct two alternative matching approaches in order to compare ATTs estimated on different samples. Table H6 shows the results across three different matching strategies for two of our main outcomes of interest — capital and total assets. Firstly, we re-estimate results using all firms matched against the discriminants of VC financing, i.e. on the sample of companies produced by the exact matching step. The second approach repeats the PSM exercise, however rather than using a calliper, we simply pick the control candidate with the nearest propensity score, irrespective of how far away it is from the treated company's score. For comparison, we also include the baseline model's results, already presented in section 5's Table 5.

Table H6: Estimated ATTs on economic size, by post-treatment period and matching estimator.

	Capital			Total Assets		
	Exact matching	PSM, no calliper	Baseline	Exact matching	PSM, no calliper	Baseline
	(1)	(2)	(3)	(4)	(5)	(6)
$ATT_{t=0}$	1.9385***	1.5898***	1.4766***	2.8703***	2.5865***	2.4350***
	(0.131)	(0.258)	(0.295)	(0.094)	(0.223)	(0.257)
$ATT_{t=1}$	2.0326***	1.5773***	1.3369***	2.8310***	2.1141***	1.8546***
	(0.125)	(0.256)	(0.300)	(0.089)	(0.200)	(0.237)
$ATT_{t=2}$	2.1520***	1.6392***	1.3777***	2.9017***	2.1012***	1.8060***
	(0.132)	(0.281)	(0.309)	(0.095)	(0.192)	(0.212)
$ATT_{t=3}$	2.2760***	2.0769***	1.6926***	2.7420***	2.3707***	2.0590***
	(0.155)	(0.316)	(0.352)	(0.113)	(0.244)	(0.288)
$ATT_{t=4}$	2.5393***	2.3896***	1.9739***	2.7631***	2.5258***	2.2397***
	(0.174)	(0.375)	(0.425)	(0.130)	(0.283)	(0.295)
$ATT_{t=5}$	2.8089***	2.4746***	2.0390***	2.5898***	2.5186***	2.3269***
	(0.201)	(0.484)	(0.525)	(0.174)	(0.350)	(0.411)
N° of observations	45,315	3,233	2,408	47,366	3,288	2,454
N° of firms	10,469	714	523	10,690	718	526
N° of treated	577	341	254	583	346	257
T-test on PS (p-value)	N/A	0.000	0.203	N/A	0.000	0.208

* 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets.

The estimates are qualitatively the same across the three different matching models. However, we see a clear quantitative contrast — treatment effects are highest in the exact matching model, decrease in the PSM model without calliper and are the lowest in the baseline model. This finding indicates that our preferred matching strategy (PSM matching with calliper) is able to significantly reduce bias and ensures that any remaining difference between our treatment and control companies is the cause of the VC financing. Furthermore, a significant difference between models (2) and (3) is how well balanced the propensity score is. PSM matching with calliper results in a distinctly more balanced sample between treatment and control firms (at the cost of almost 100 treated companies, however), which is another reason for its superiority in comparison to the alternatives.

We conclude that while applying the identified discriminants of VC-financing already produces significant positive results, accounting for further predictors allows us to more precisely isolate the VC investment treatment effects. The difference pattern among the three models applies to the rest of the outcomes of interest presented in section 5 as well.

Heckman Selection model

The final sample of treated companies used for our analysis has shrunk more than three times from the initial population of EIF VC-backed start-ups. Unfortunately, we are unable to include the entire population in the final regressions since not all firms have available data or were matched with a control.[66] In order to ensure the estimated effects are not the result of selection dynamics underlying the data unavailability issue, we employ the Heckman selection model (Heckman, 1979).

The Heckit method, as it is also known, allows for the correction of potential selection bias following a two-step procedure. Firstly, we estimate the probability of each firm to remain in the final sample by constructing a selection equation and employing a probit regression.[67] Next, we incorporate a transformation of these predicted probabilities (the so-called Inverse Mills ratio) for each firm, which is then included in the final regressions as an additional explanatory variable to correct for selection.

Table H7 presents the effects on our main outcomes of interest re-estimated using the Heckman model. The results remain strongly significant and quantitatively very similar. This finding reassures us that the identified positive effects are not driven by non-random selection bias.

Table H7: Estimated average treatment effects on the treated, by post-treatment period (Heckman correction).

	ln (Capital) (1)	ln (Tot. assets) (2)	ln (Revenues) (3)	ln (Op. costs) (4)	ln (Staff costs) (5)
$ATT_{t=0}$	1.2752***	2.3779***	-0.7549*	0.9935***	0.6518*
	(0.327)	(0.263)	(0.355)	(0.282)	(0.304)
$ATT_{t=1}$	1.3164***	1.8636***	0.0299	1.4221***	0.4919
	(0.326)	(0.236)	(0.323)	(0.305)	(0.311)
$ATT_{t=2}$	1.4425***	1.8811***	0.7105*	1.4975***	1.0057**
	(0.338)	(0.230)	(0.331)	(0.347)	(0.312)
$ATT_{t=3}$	1.6858***	2.0889***	0.7003†	1.4719***	1.0631**
	(0.395)	(0.290)	(0.388)	(0.388)	(0.377)
$ATT_{t=4}$	1.9285***	2.3074***	0.6746†	1.6922***	0.9164*
	(0.454)	(0.307)	(0.403)	(0.394)	(0.368)
$ATT_{t=5}$	1.8131**	2.2766***	0.8753†	2.0057***	0.9171†
	(0.550)	(0.395)	(0.485)	(0.421)	(0.481)
Inv. Mills ratio	3.9569	1.8110***	-0.1033***	-0.0185	-0.0466
	(0.627)	(0.255)	(0.356)	(0.305)	(0.265)
N° of observations	2,408	2,454	1,250	1,034	948
N° of firms	523	526	372	298	273
N° of treated	254	257	159	131	125
T-test on PS (p-value)	0.203	0.208	0.071	0.139	0.140
Prop. of strata covered	0.464	0.464	0.464	0.464	0.464

† 0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets.

Quantile analysis

By estimating the average treatment effects we are unable to observe whether VC financing has a different effect depending on company size. The ATTs presented in section 5 could potentially be

66 The main reason for the significant data loss is the lack of information relating to the start-up team — propensity score is available for only 63% of the initial population.

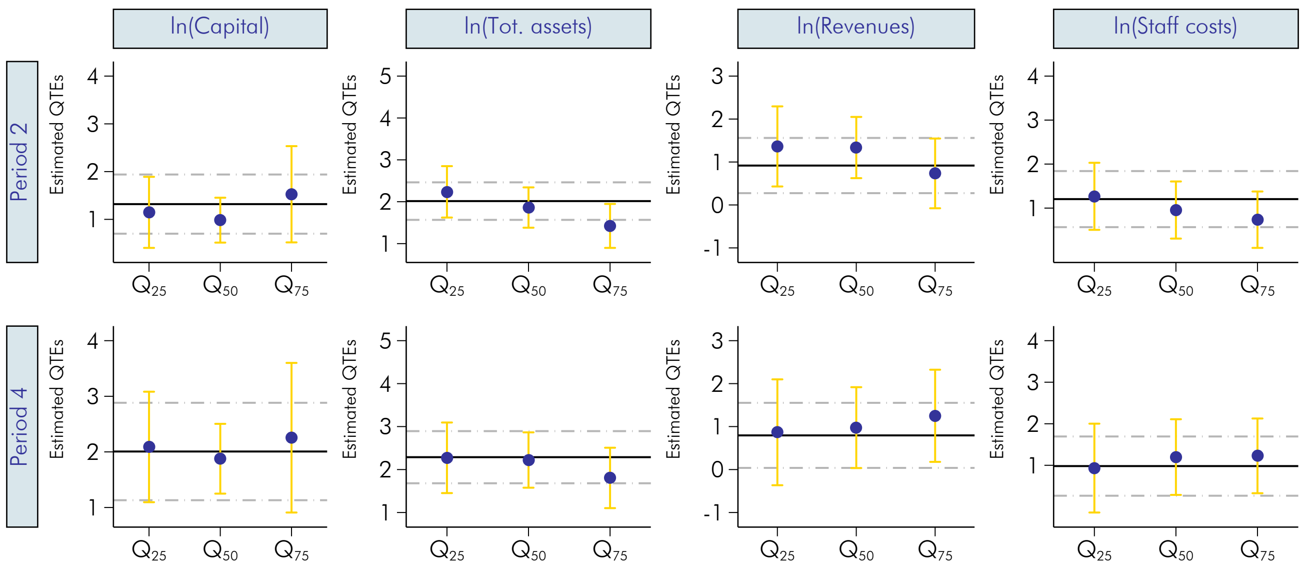
67 We estimate the probabilities based on the initial population of EIF VC-backed start-ups (782) plus an additional set of 18 firms which could not be identified in the Orbis database.

concealing a heterogeneous impact across the distribution of firms. Particularly in the case of public policy evaluation, it is important to go beyond averages and study interventions' distributional effects. For this reason, we employ a quantile treatment effects (QTEs) analysis (Koenker and Bassett, 1978), which can reveal the impact on different parts of the distribution of our dependent variables.

Before discussing the results, it is important to note that quantile effects are defined as differences between quantiles of the two marginal potential outcome distributions, rather than as quantiles of the unit level effect. That is, the applied conditional quantile regression (as opposed to unconditional quantile regression) estimates the effects on distributions instead of companies.[68]

Figure H4 presents the QTEs together with the 95% confidence intervals of our baseline ATTs concerning four economic size indicators, in periods $t = 2$ and $t = 4$.[69] We split the data in quartiles and show the estimates for, respectively, the 25%th, 50%th and 75%th percentiles. We do not detect significant differences between the quantile treatment effects and the average treatment effects, nor among the different quantile effects themselves at the 5% significance level.[70] These findings are clearly flagged by Figure H4, where the confidence intervals of all QTEs always overlap.

Figure H4: Quantile and Average Treatment Effects



Note: QTEs point estimates shown as blue dots; 95% confidence intervals for QTEs in yellow. For comparison, ATT point estimates shown as continuous black intercepts, and their 95% confidence intervals shown as dotted grey lines.

The analysis shows that the treatment induces a simple location shift of the distribution, rather than a location-scale shift. In other words, VC investment has a homogeneous effect over the distribution of the presented firm size indicators and there is no subset of firms significantly advantaged. This is an important finding implying that VC financing does not disproportionately advantage, for instance, higher capitalised firms, since the effect remains the same at both ends of the variable's distribution.

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68 Note that, should VC financing positively affect the lower quantile of the revenue distribution, this would not necessarily imply that companies with lower turnover levels would now be generating more sales. It merely indicates that treated companies relatively less capable to generate revenue gain more in comparison to their counterfactuals, which are similarly located in the lower quantile of the distribution.

69 We obtain similar results for the remaining three periods.

70 Results remain unchanged also for the 1% and 0.1% significance levels.

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