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The European venture capital landscape: an EIF perspective

Volume VI:
The impact of VC on the exit and innovation outcomes of EIF-backed start-ups

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Abstract[†]

We use competing risks methods to investigate the causal link between venture capital (VC) investments supported by the EIF and the exit prospects and patenting activity of young and innovative firms. Using a novel dataset covering European start-ups receiving VC financing in the years 2007 to 2014, we generate a counterfactual group of non-VC-backed young and innovative firms via a combination of exact and propensity score matching. To offset the limited set of observables allowed by our data, we introduce novel measures based on machine learning, network theory, and satellite imagery analysis to estimate treatment propensity. Our estimates indicate that start-ups receiving EIF VC experienced a significant threefold increase in their likelihood to exit via M&A. We find a similarly large effect in the case of IPO, albeit only weakly significant. Moreover, we find that EIF VC contributed to a 13 percentage points higher incidence in patenting activity during the five years following the investment date. Overall, our work provides meaningful evidence towards the positive effects of EIF's VC activity on the exit prospects and innovative capacity of young and innovative businesses in Europe.

Keywords: EIF; venture capital; public intervention; exit strategy; innovation; start-ups; machine learning; geospatial analysis; network theory

JEL codes: G24, G34, M13, O32, O38

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Non-technical Summary

This study constitutes the sixth volume of the working paper 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 exit prospects and innovative capacity of start-ups. Accordingly, this work compares the exit outcomes and patenting activity 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 trajectory of treated firms had they not received VC. This paper's empirical approach is based on a previous work in the series (Pavlova and Signore, 2019).

Constructing an appropriate control group for VC-backed firms entails several challenges. Our previous work addressed these by mapping the entire set of European VC-invested start-ups in the years 2007 to 2014. The exercise was enabled 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, provide an unrivalled coverage of the European VC ecosystem. We further rely on Bureau Van Dijk's Zephyr and Orbis databases to retrieve exit outcomes and patenting data respectively. By combining Invest Europe's and Bureau Van Dijk's data, we create a novel dataset tracking all European start-ups backed by VC in 2007–2014 (see Crisanti *et al.*, 2019 for details).

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, in Pavlova and Signore (2019), we carried out an extensive review of the literature to build a comprehensive model of VC contracting. However, given that our data sources do 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 backdrop, in our previous work we brought our model to the data by introducing measures based on machine learning, network theory and satellite imagery analysis, some of which were original to the VC literature.

In this work, we combine the above-mentioned metrics with multiple other predictors of VC financing to construct our estimator, based on exact and propensity score matching. Given that a successful exit outcome depends both on the type of exit route and the timing of the exit decision, we resort to survival/duration models to appropriately describe the characteristics of our data. Specifically, we use competing risks analysis, which provides a model for time until a certain exit event. Competing risks analysis measures the occurrence over time of exit events that are mutually exclusive.

Our results confirm the positive effects of EIF-supported VC investments on the probability that start-ups experience a favourable exit outcome. We find that EIF VC-invested start-ups were about three times more likely to participate in an M&A deal than their non-VC invested counterfactuals. In absolute terms, this entails a 10.3 percentage points (pp henceforth) higher probability of M&A for VC-backed start-ups, five and a half years after the investment date. EIF VC-invested start-ups were also about three times more likely to experience an IPO compared to their counterfactuals — entailing a 1.7 pp higher IPO rate by the fifth post-investment year. However, due to the relatively infrequent occurrence of IPOs in our sample, this result is only weakly significant. We do not observe significant effects of EIF VC on bankruptcy, nor on other forms of buy-outs, though this might be due in part to the low statistical power of some of our tests.

Exploiting M&A as the predominant exit outcome for EIF VC-invested start-ups, we set-up additional regressions that distinguish between different types of M&A deals, i.e. horizontal/vertical integrations or diversifications, or national/international M&A deals (based on the headquarters' location of start-ups and buyers). We find that EIF VC had a strong and significant effect on the likelihood to experience both a horizontal and vertical integration, with a threefold and sixfold increase in the probability of each M&A outcome respectively. By contrast, the effect on diversifications was not apparent. We also find that EIF VC brought an almost sixfold increase in the chance to experience international acquisitions, while it had a much more muted effect on the incidence of national M&A.

The findings are consistent with the theory that the presence of VC investors opens up additional exit channels that would not otherwise be available to the entrepreneur. In our sample, this translated into a disproportionally positive impact on horizontal and vertical integrations. Moreover, as shown in the literature (Bertoni and Groh, 2014), this effect might be further amplified by the presence of numerous cross-border investments in our sample. In turn, the significant share of cross-border investments might explain the disproportionally positive impact on the likelihood to experience M&As with at least one foreign buyer. Phillips and Zhdanov (2017) show that an active M&A market provides an incentive for VC firms to engage in more VC deals, supporting the hypothesis that the EIF fostered a virtuous cycle between VC activity and the exit environment.

As mentioned above, this paper also looks at the effects on the innovation capacity of start-ups. We find that EIF VC contributed to a doubling of the likelihood to patent, compared to counterfactuals. In absolute terms, we find a 10 pp higher probability to patent for EIF VC-backed start-ups, already by the second post-investment year — further up to 13 pp six years after investment. Our findings are consistent with the theory that VC alleviates the financial constraints of young innovative businesses and allows them to maintain high R&D expenditures and cover the direct and indirect costs of patenting (Bertoni *et al.*, 2010). In addition, monitoring by VC firms might prove a direct incentive towards patenting or, by promoting financial discipline, indirectly foster the start-up's innovative capacity.

In summary, we observe higher IPO and M&A rates for start-ups supported by the EIF compared to similar, non-VC-backed firms. This is likely due to VC firms opening up additional exit channels that would not otherwise be available to the entrepreneurs. EIF VC also contributed to higher patenting rates for beneficiary start-ups. This might be due to the mitigation of financial constraints as well as the tighter financial discipline induced by VC firms. These findings, in line with current economic research, point to the effectiveness of EIF's policy instruments fostering SMEs' access to VC financing.

Overall, our work supports the development of an "impact culture" by discussing the causal effects of VC financing supported by the EIF. Our study provides meaningful evidence towards the positive role of EIF VC on the exit prospects and innovation capacity of young innovative businesses in Europe.

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1 Introduction

Venture capital can be an essential source of financing for wealth-constrained entrepreneurs that pursue an innovative business idea. In a typical scenario, VC firms invest in start-ups via the acquisition of equity shares in the company. These shares are characterised by very low liquidity, in particular during the business's initial development phase. In addition, these shares rarely yield dividends, notably if the firm's business model has not yet delivered a positive cash flow. Therefore, the future re-sale of the company shares may well be the only recourse VC firms have to profit from their investments. Most often, this profit stems from the start-up's creation of value through innovation.

Two elements stand out from our stylised description of VC investing. First, the exit decision is a critical step in the VC investment life cycle, equally important to the entry decision itself (Schwienbacher, 2012). Exit performance serves as a signal of the VC firm's quality. Moreover, exit conditions can have a lasting effect on key business decisions (e.g. R&D investments) and the overall growth of VC-backed start-ups (Meles *et al.*, 2014). Second, the VC investment decision is based on the start-up's pledge to create value through high-risk/high-reward innovative entrepreneurial ideas.

A key question is whether and how VC investing affects the prospects of innovative start-ups. In Pavlova and Signore (2019), we addressed this topic from the standpoint of the economic and financial growth of VC-backed start-ups. This paper further contributes to this discussion by investigating the causal link between VC investing and the exit patterns of start-ups supported by the EIF in the years 2007-2014. In addition, we examine the causal role of VC investing on the innovation capacity of beneficiary start-ups, as measured via their patenting activity.

The benefits of a thriving VC ecosystem are well known (see e.g., Bertoni *et al.*, 2011; Colombo *et al.*, 2014). Consequently, over the last two decades the EIF has strived to pursue its policy-oriented goal to support the formation of a resilient European VC ecosystem and the emergence of new European VC hubs. This partly explains the EIF's current prominent role in the European VC landscape. Kraemer-Eis *et al.* (2016) argue how this calls for a thorough assessment, to verify if the initial policy targets were met. In this respect, our work complements the series of EIF working papers "The European venture capital landscape: an EIF perspective", which is centred around this topical question.

The EIF fulfils its public policy mission by investing its own funds as well as 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. In this context, the EIF predominantly adopts an intermediated model, which entails the acting as a limited partner (LP) in privately managed VC funds (Alperovych *et al.*, 2018). EIF investments in VC funds follow a detailed due diligence process, focussing on various aspects of the investment proposal. Additional scrutiny is paid to the quality of the VC firm's team, to their ability to adhere to the EIF's policy goals and to contribute to the growth of portfolio companies while, at the same time, generating returns consistent with market conditions.

The paper is organised as follows. Section 2 provides an overview of the relevant empirical literature. Section 3 discusses the source and characteristics of our data. Section 4 illustrates the empirical approach, which is largely based on our previous work (Pavlova and Signore, 2019). Section 5 presents selected summary statistics, while section 6 discusses our empirical findings. Section 7 concludes.

2 Literature review

2.1 Venture capital and exit outcomes

The evaluation of exit options is a crucial part of VC firms' investment appraisal process. Two key elements contribute to a successful exit decision: the timing of the exit and the type of exit route. The economic literature mainly focuses on three types of VC exit routes: initial public offering (IPO), trade sale (i.e. merger and/or acquisition), or liquidation (Da Rin *et al.*, 2013). Additional exit routes include — but are not necessarily limited to: management buy-in/buy-out (or share buyback), institutional buy-out (or secondary sale). Throughout this paper, we refer to these exit routes as "Other buy-outs".

Due to challenges related to the availability of both unbiased data and an appropriate identification strategy, the empirical literature investigating the causal relationship between VC investing and start-up exit events is rather limited. Nevertheless, the existing body of research provides compelling insights. We provide here a brief overview.

After controlling for companies' asset volumes, Bottazzi and Da Rin (2002) find that venture-backed firms raise on average 60% more than non-VC-backed firms during an IPO. Brav and Gompers (1997) also confirm that venture-backed IPOs outperform non-venture-backed IPOs using equal-weighted returns. However, they note that value-weighting significantly reduces performance differences. Their study suggests that IPO under-performance for non-VC-backed firms might stem from the entrepreneurs' lack of market information. An alternative hypothesis for this discrepancy relates to the existence of strategic partnerships, facilitated by VC firms. Venture-backed firms exploiting such strategic alliances tend to be associated with a higher probability of successful exit (Lindsey, 2008).

Megginson and Weiss (1991) identify the presence of VC certification for US-backed start-ups, i.e. VC-backed companies elicit greater interest from institutional investors during the IPO phase, and also tend to go public earlier than matched non-VC-backed firms. The VC certification hypothesis was questioned by Jelic *et al.* (2005), then confirmed again by Dolvin (2005).

In their exhaustive study, Puri and Zarutskie (2012) compare a matched sample of VC and non-VC-financed firms in the US. Descriptive statistics on the exit performance of VC-financed firms show that 39.7% failed, 33.5% were acquired, and 16.1% went public. In contrast, non-VC-financed firms performed considerably worse — 78.9% failed, 1.04% were acquired, and only 0.02% went public. Chemmanur *et al.* (2008) also show that VC backing and the associated efficiency gains positively affect the probability of a successful exit.

Hsu (2006) finds that relative to a control group, VC-backed companies are more likely to engage in cooperative commercialisation strategies, such as strategic alliances or technology licensing. They also have increased likelihood of IPO, especially if financed by more reputable VC firms (VCs). Strategic alliances and VC financing both increase the likelihood of going public among young biotech companies (Ozmel *et al.*, 2013).

A strand of literature has looked at the exit performance of firms backed by either governmental VC support or independent VC firms' investments. Colombo *et al.* (2014) provide an excellent synthesis of current research, which appears to converge to a mostly consistent set of findings discussed below.

Cumming *et al.* (2017) find that mixed independent-governmental syndicated VC investments lead to a higher likelihood of successful exit outcomes than independent[1] or purely governmental VC-backed (GVC) investments in Europe. Similar conclusions emerge from a study of Australian start-ups, where a blend of independent and government VCs resulted in a higher share of publicly listed investments as well as larger market capitalisation (Cumming and Johan, 2014). Brander *et al.*'s (2014) findings from a large international sample confirm that GVCs are beneficial to successful exits only when they syndicate with private VCs and when private VCs provide a large fraction of the funds.

Buzzacchi *et al.* (2015) note that while independent VC firms have an incentive to divest low-return investments as soon as they can, EIF co-invested VC firms tend to delay an exit if start-ups are likely to generate social returns or exert a positive impact on the economic system, even if their return prospects might be sub-optimal. The authors argue that this evidence is compatible with the overarching goal of a public investor, which is not restricted to financial returns, but also includes additional factors related to the spillover effects of entrepreneurship. See also Kraemer-Eis *et al.* (2016) on this topic.

On the one hand, the above studies point to mixed private and public VC bringing about the most positive results. On the other hand, these studies also assert that pure governmental VC tends to yield much weaker effects. This finding is further supported by Cumming and Johan (2008), who find that government VC-backed companies are less likely to experience an IPO and/or acquisition exit route, but rather a secondary sale and/or a buyback.

In conclusion, we find our brief survey of the literature in line with Da Rin *et al.*'s (2013) extensive review. Da Rin *et al.* (2013) argue that the evidence of VC-backed companies achieving better exit outcomes than other start-up categories is significant. When VC-backed firms are further classified based on the type of supporting VC firm — governmental, independent or mixed — data suggest that a combination of private and government VC leads to a higher chance of successful exit events.

2.2 Venture capital and innovation

A multi-decade literature has looked at the relationship between innovation and VC, trying to establish the direction of causality. There are currently two main schools of thought: the first argues that VC firms nurture, encourage and stimulate start-ups to exploit their innovative potential. We call this strand "VC first". The "innovation first" school claims instead that VC firms merely scout for highly innovative ideas, which in turn show an intrinsically higher chance to benefit from e.g., patenting. Most studies lean to either of the two hypotheses. We provide here an informative, yet in no way complete, survey of the existing literature.

Kortum and Lerner (2000) were among the first to examine the effect of venture capital on innovation. By using both firm- and industry-level US data as well as different measures related to innovation, such as patent renewals and intellectual property litigation, they found that VC significantly increases the patenting rate in a given industry.

Several studies analysed the Spanish VC market. Alemany and Martí (2005) contribute to this research by studying an alternative measure of innovation, i.e. net investment in intangibles. The authors find

[1] However, the difference between mixed and independent VCs' investments is not statistically significant.

that the intangible assets of VC-backed companies grew at a faster rate compared to those of similar firms that did not receive a VC investment. Additional evidence from the Spanish market can be found in Bertoni *et al.* (2010), who find that VC investments positively affect subsequent patenting activity. The authors note that before receiving the financing, VC-backed firms did not exhibit a significantly higher propensity to patent compared to other firms.

Similarly, using a large set of controls, Arqué-Castells (2012) concludes that firms increase their patenting activity after a VC investment. The author's main result holds over a wide range of model specifications, supporting the case that the sharp increase in patenting following the VC financing is caused by a positive treatment effect, rather than a pure selection effect. Arqué-Castells (2012) further argues that the higher patenting activity is not the mere result of start-ups' increased capital availability to, inter alia, patent pre-existing innovations. In fact, VC firms appeared to fund and support the entire innovation development process.

In the US, the prominent role of VC in fostering innovation is further shown by Dushnitsky and Lenox (2005) and Popov and Roosenboom (2009). The authors find a significant positive effect of risk capital finance on innovative activity. VC is also found to help Dutch-based portfolio companies develop absorptive capacity and durably increase their in-house R&D (Da Rin and Penas, 2007).

Lastly in this strand of literature, Bertoni and Tykvová (2015) analyse European biotechnology start-ups and note that the combined effect of independent and governmental VC syndicates is more than the sum of its parts' individual effects. The authors estimate a positive effect of independent and governmental VC syndicates both for the case of invention (measured through unweighted patent stock) and innovation (measured through citation-weighted patent stock).

The "innovation first" school argues in favour of reverse-causality, whereby innovations induce VC and not vice-versa. By comparing German VC-financed start-ups to an identical group of firms without VC backing, Engel and Keilbach (2007) find that VC firms target the more innovative start-ups. At the same time, the authors did not find that VC-funded firms produce more innovative output than similar non-VC-backed start-ups. In addition, Caselli *et al.* (2009) conclude that innovation plays a key role during the selection process, however VC does not foster innovation activity per se.

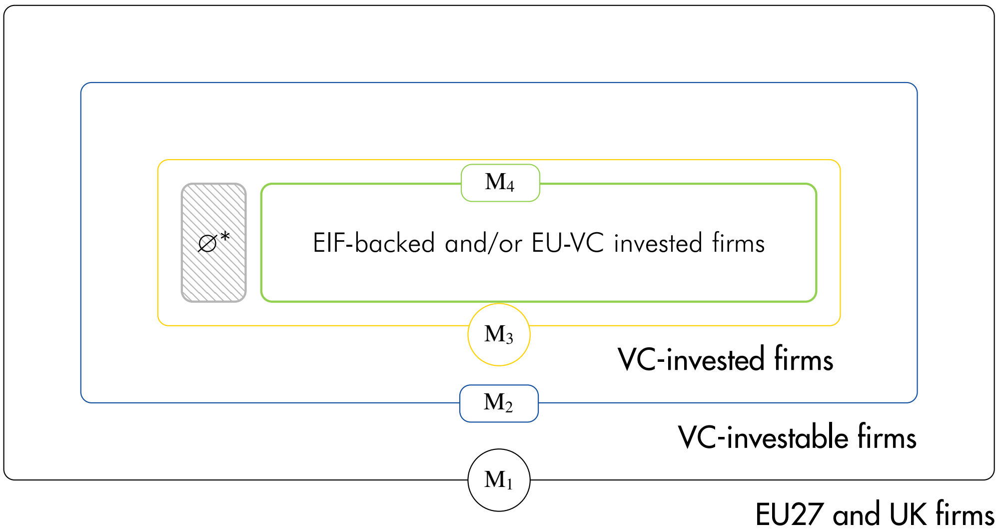
Although Hellmann and Puri (2000) also conclude that companies showing higher innovation activity are more likely to receive VC, they still find that the presence of VC is positively associated with a significant reduction of the time a company needs to introduce its products to the market. Conversely, Stuck and Weingarten (2005) and Peneder (2010) find that VC has no causal impact on innovation output when comparing VC-backed with similar non-VC-backed companies in North America and Austria respectively. In fact, contrary to the result of Arqué-Castells (2012) presented above, Peneder (2010) concludes that any difference related to innovation must be directly caused by selection effects.

The "innovation first" hypothesis is further backed up by three studies analysing the European and US industries, which find no indication of VC's positive influence on innovation activity (Geronikolaou and Papachristou, 2012; Hirukawa and Ueda, 2011; Arvanitis and Stucki, 2012). In conclusion, both theories find significant support in the literature and further research might be necessary to identify the true direction of causality.

3 Data and Methods

This section provides a brief summary of the features as well as the main assumptions underlying our data. In the absence of an EIF-backed VC investment, we assume that a wealth-constrained entrepreneur would resort to alternative financing channels. As a result, a central problem of our study is the identification of start-ups that failed to obtain VC.[2] In Pavlova and Signore (2019), we discuss a practical solution to this issue, illustrated in Figure 1 through nested conditional sets.[3]

Figure 1: Identification of treatment and control populations[4]



* The conditional empty set ∅ emphasises the data completeness assumption for M_4. Source: Pavlova and Signore (2019).

Our approach requires a representative dataset for the population of EU27 and UK firms along with a complete listing of VC-invested start-ups in the region. We select Bureau Van Dijk's Orbis database as a suitable approximation for the population of firms in the EU27 and UK.[5] In addition, Orbis serves as the main source of industry, financial performance, human capital and patent data.

The source of our near-complete mapping of start-ups in the European VC ecosystem is an extensive data collection exercise carried out by Invest Europe — the association representing Europe's Venture Capital and Private Equity industry.[6] Whenever necessary, we integrated this collection with EIF's own activity data. See Crisanti *et al.* (2019) for a description of this dataset. We further converted this mapping into a list of business legal entities available in Orbis, based on a rigorous identity-matching process — controlling for e.g., company name, location, sector, date of incorporation and fiscal ID.

We do not discuss here the ability of our data to correctly identify start-ups that failed to obtain VC. Interested readers can refer to section 3 of our previous work (Pavlova and Signore, 2019). Instead,

2 These form the basis for the counterfactual (or control) group. We discuss its construction in section 4.

3 The condition being that each element of each set of Figure 1 must be observable in the Orbis database.

4 If not stated otherwise, figures and tables are from the authors, based on EIF and Invest Europe data.

5 Orbis is an aggregator of firm-level data gathered from over 75 national and international information providers, such as e.g., business registers, credit bureaus, national banks, statistical offices. As of December 2020, Orbis tracks 390 million companies in over 90 countries. Less than 0.01% of these are listed.

6 Given that Invest Europe's data are sourced directly from affiliated VC firms, they provide to the best of our knowledge an unrivalled coverage of the European VC ecosystem.

we provide here a brief complementary discussion on the suitability of our approach, entailing a comparison of start-ups receiving EIF VC against start-ups that failed to obtain VC. An important caveat that stems from our empirical design is that we can only identify the cumulated effect of VC investments and the (potential) policy-driven contribution of the EIF. By contrast, we are unable to isolate any differential effect directly attributable to the presence of the EIF in a given VC investment. In principle, a comparison between EIF VC and other-than-EIF VC investments could overcome this limitation. However, the characteristics of our dataset prevented us from further pursuing this avenue.[7]

Given that we could only identify in Orbis a small share of the population of VC-backed start-ups prior to 2007, the focus of our work is on those invested during 2007-2014, i.e. when our coverage is near-complete. We further narrow down our research to firms in the seed and start-up investment stages, grouped under the collective term "early stage" (Jeng and Wells, 2000). Finally, we only look at start-ups supported by EIF VC investments, which confines our initial treatment group to 782 EIF VC-backed firms. Table 1 summarises the process leading to our final set of treated firms.

Table 1: VC-invested firms breakdown

Sample	Number of firms
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	4,945
- of which EIF	782

Source: Pavlova and Signore (2019).

The first outcome of interest in this paper is the exit type of VC-financed firms. We source exit information from Bureau Van Dijk's Zephyr database, which as of December 2020 contains information on over 2.1 million worldwide merger and acquisition (M&A henceforth), IPO, private equity and VC deals. While Zephyr might fail to provide the most exhaustive set of exit deals (Bollaert and Delanghe, 2015), it bears the advantage of assigning every deal to one or more participating legal entities in the Orbis database, which greatly facilitates our data collection. Crucially, a Zephyr deal might be directly assigned to the legal entity of the company under scrutiny and/or indirectly assigned via a controlling entity. Therefore, when treating these data it is essential to account for the (time-varying) structure of the start-up's corporate group. We detail the compilation of exit data in Appendix A.

Our second outcome of interest is the start-ups' innovation activity. We measure firms' innovation efforts based on the count of patent applications, sourced from Orbis and PATSTAT (see Signore and Torfs, 2017 for details about the data). Specifically, we use patent families as units of measure — "a patent family is a collection of related patent applications that is covering the same or similar technical content" (European Patent Office, 2017).[8] Patent families are regularly employed as unit of analysis when the research focus is on firms' inventions (Hall, 2014). Moreover, this approach is consistent with previous works in the EIF working paper series.[9] Nevertheless, we acknowledge that there are multiple caveats in using patenting as a proxy for innovation (see e.g., Lerner, 2002).

[7] Specifically, the lack of information concerning investment volumes and investor information for the other-than-EIF VC sample would not allow us to control for the EIF's non-random selection of VC funds (see section 1), leading to a flawed empirical strategy and biased estimates of the EIF's differential effect.

[8] We sort innovations according to the date of application (as opposed to, if applicable, the date of granting).

[9] Analogously to Signore and Torfs (2017), this work employs patent family ownership, as opposed to registration, as the main unit of analysis. The key difference is that the former can be transferred between entities

4 Empirical Approach

This section outlines our empirical strategy to identify the effect of a VC investment on the start-up's exit outcome and innovation output. The approach entails a minor extension to the methods we presented in Pavlova and Signore (2019), for which we provide a brief summary below. Interested readers are referred to section 4 of our previous work for a detailed discussion. Henceforth, VC-invested start-ups supported by the EIF in the period 2007-2014 will be referred to as the treatment group, while non-VC-backed firms will be called counterfactuals or controls.

4.1 Identification strategy

Our empirical strategy is based on Rubin's Causal Model and the potential outcomes framework (Rubin, 1974, hereafter RCM).[10] Under RCM, the potential outcome experienced by VC-backed firms in the absence of VC financing (unobservable) can be replaced by the potential outcome experienced by appropriately selected non-VC-backed firms (observable). In other words, our counterfactual group simulates the outcome of VC-backed firms had they not received VC, and the difference between the two groups' outcomes represents the effect of VC financing.

The construction of a suitable control group relies on a thorough understanding of the decision-making process of venture capitalists. To this end, in Pavlova and Signore (2019), we undertook an extensive literature review with the goal to enumerate factors that might affect VC contracting. We identified two types of factors: a) discriminants and b) predictors of VC contracting. Discriminants of VC financing are high-level features that characterise the firm's operations. These are used to assess the viability of a VC investment opportunity as well as its exit prospects. They include principal features at investment date, namely the start-up's country and sector of operations, its age, whether it had applied for a patent and its degree of innovativeness. Predictors of VC financing represent factors that are more likely to be "traded-off" during the investment appraisal process. These are related to the entrepreneurial team — team size, founders' age, previous experience, gender and nationality.

Two additional variables complete the set of predictors of VC financing in Pavlova and Signore (2019). The first is a proxy for VC demand and constitutes a predictor of housing demand elasticity: based on the considerations in Robb and Robinson (2014), entrepreneurs located in urban areas with stable-valued dwellings — easily pledgeable as collateral to lenders — might show lower appetite for external equity finance. The second measure is a proxy for the supply of venture capital: based on the observations in Lerner (1995) and Bernstein *et al.* (2015), VC firms' investment decisions are sensitive to geographical distance. We exploit this knowledge to construct a measure of start-up "accessibility" with respect to the population of active VC firms in a given year.

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following the acquisition of firms and/or their intellectual property (IP). Thus, this work does not distinguish between acquired and originated IP, as the two R&D strategies can be equally effective in the creation of new innovative capacity. Using an extended version of our dataset covering pre-2007 EIF VC investments, Signore and Torfs (2017) find that for 86% of innovations the legal entity of the original applicant and of the owner coincide. That is, most innovations were (in all likelihood) developed internally by the start-ups.

[10] RCM rests on three key assumptions: a) stable unit treatment value; b) unconfoundedness; c) overlap. See Pavlova and Signore (2019) for a detailed discussion and implications for the case of VC-backed start-ups.

In this paper, we add three new predictors to the treatment assignment model in our previous work. Not only these improve our treatment assignment predictions, but are also likely to contribute to the start-up's exit outcome. The additional predictors concern the start-up's corporate structure at the time of investment. Namely, we include a count of the start-up's controlling firms,[11] an indicator of the start-up's independence (i.e. to autonomously set its strategic direction) and the level of ownership concentration (i.e. no shareholders, corporate majority shareholder, corporate plurality shareholder, non-corporate majority/plurality shareholder). Appendix A details the construction of the indices.

We follow the approach in our previous work (Pavlova and Signore, 2019) to construct and implement our matching estimator. In essence, it corresponds to the estimator described in Abadie and Imbens (2006), implemented via a combination of exact- and propensity score-based matching. The two-step matching approach mirrors the stylised treatment assignment process described above. Each start-up is first "screened", a process we mimic via exact matching, on the discriminants of VC financing.

The investment decision stage is further simulated by our propensity score matching model, which includes both discriminants and predictors of VC financing. As in our previous work, we estimate the propensity score with a multi-level mixed effects model, which appropriately accounts for the hierarchical nature of our data: entrepreneurs nested within start-ups, themselves clustered in urban areas. Moreover, we follow our previous work and estimate the propensity score model using our complete dataset of European VC-invested firms in the years 2007-2014 (i.e. including non-EIF-backed investees) and candidate controls, in order to maximise the model's predictive ability. It is important to note that this approach implicitly assumes that the VC assignment mechanism is independent from the selection process of the EIF (see section 1 and 3). In other words, we assume that there are no significant differences between the likelihood of obtaining EIF VC and other-than-EIF VC.[12]

Table 2 reports the Odds Ratios (ORs) and goodness of fit of our propensity score model. ORs describe the odds that an outcome will occur given a particular exposure, compared to the odds of the outcome occurring in the absence of said exposure (Szumilas, 2010). An OR > 1 implies that the exposure is associated with increased odds to observe the outcome, while OR < 1 implies the opposite. For instance, if OR $= 2$ for a binary covariate d, this means that the outcome is twice as likely to occur if start-ups have $\mathrm{d} = 1$ than if they have $\mathrm{d} = 0$.

All covariates are either strongly significant, significant or close to the 10% significance level. We use the model's predicted scores to identify the counterfactual firm for every VC-invested start-up. The counterfactuals in our baseline model are identified via a one-to-one nearest neighbour matching with replacement and calliper. [13] Table 3 provides descriptive statistics of the pre-treatment attributes in the final matched sample, separately for treated and controls — T and C respectively. Column 5 of Table 3 provides the p-value of mean-comparison t-tests for each included variable, confirming the adequate balancing ability of our estimator.

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[11] Controlling companies are defined as entities with a 50% or higher participation share in the start-up.

[12] Buzzacchi *et al.* (2013) argue that this might be a strong assumption. However, our data does not provide strong evidence that EIF VC is administered differently than non-EIF VC when looking at homogeneous groups of start-ups — e.g. as identified through cluster analysis.

[13] Our baseline approach sets the calliper as the standard deviation of the treated firms' propensity scores.

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

	Pr (treatment = 1)
	MULTI-LEVEL MIXED EFFECTS LOGIT
Founding team size‡	1.8622***
	(0.086)
Age of founding team‡	0.9531***
	(0.010)
Previous founding experience‡	3.9512***
	(1.360)
Foreign-born entrepreneurs‡	0.9081**
	(0.030)
Female entrepreneurs‡	0.1326***
	(0.033)
Firm age at inv. year	0.8908***
	(0.014)
Patent at inv. year	3.2436***
	(0.425)
Predicted degree of innovativeness	1.8180**
	(0.359)
Firm accessibility score	1.2528
	(0.175)
ln (Firm's distance from closest FUA× centroid)	0.8817***
	(0.011)
ln (FUA's undevelopable land)	0.3755
	(0.232)
Number of shareholders	0.4899***
	(0.068)
Independence Indicator:α (omitted: A)	
B	1.0518
	(0.114)
C	0.1708***
	(0.078)
D	0.3593***
	(0.038)
Unknown	1.8455***
	(0.169)
Group ownership type: (omitted: No shareholders)	
Corporate majority shareholder	1.7970***
	(0.150)
Corporate plurality shareholders	1.3108**
	(0.136)
Non-corporate majority/plurality shareholder/s	0.6000
	(0.334)
Constant	0.0042***
	(0.003)
Cluster means (pooled)	4.9063
	(8.843)
Quadratic terms (pooled)	0.0009***
	(0.001)
Cubic terms (pooled)	2.0452
	(3.096)
Interactions (pooled)	0.2102**
	(0.109)
Investment Year Fixed Effects	Yes
Start-up macro-industry Fixed Effects	Yes
Start-up macro-region Fixed Effects	Yes
Log-likelihood	-6167.16
Obs.	31,989
Pseudo-R^2 (McKelvey and Zavoina, 1975)	0.41
Area under the ROC curve	0.872

† 0.10 * 0.05 ** 0.01 *** 0.001; ‡ Founder-level characteristic; Exponentiated coefficients (std. errors in brackets);

× Functional Urban Area, i.e. a densely populated area and its neighbouring commuting zones (OECD, 2012);

α A: No shareholder with ≥ 25% ownership; B: No shareholder with ≥ 50% ownership, but at least one with ≥ 25%; C: A shareholder with ≥ 50% ownership and/or an ultimate owner exists, D: A shareholder with a direct ≥ 50% ownership.

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	274	274	40.81	41.90	40.29	42.34	8.446	8.226	0.126
Share of female team members	274	274	0.10	0.11	0.00	0.00	0.193	0.199	0.531
Share of foreign team members	274	274	0.17	0.15	0.00	0.00	0.275	0.310	0.606
Average team prev. experience	274	274	42.04	22.08	1.88	1.00	434.9	227.5	0.501
Founding team size	274	274	4.28	4.19	3.00	3.00	3	3	0.741
Firm age at inv. year	274	274	2.07	2.02	1.36	1.36	1.868	1.817	0.776
Patent at inv. year	274	274	0.20	0.20	0.00	0.00	0.404	0.404	1.000$^{\varphi}$
Predicted degree of innovativ.	274	274	0.59	0.59	0.91	0.92	0.436	0.434	0.975
Firm accessibility score	274	274	1.24	1.15	0.45	0.38	1.644	1.654	0.536
ln (Firm distance from FUA centroid)	274	274	-0.78	-0.84	-2.30	-2.30	2.308	2.352	0.767
ln (FUA's undevelopable land)	274	274	-2.95	-2.97	-3.43	-3.39	1.023	1.083	0.792
Number of shareholders	274	274	0.19	0.19	0.00	0.00	0.521	0.600	1.000
Investment period:									
2007-08‡	274	274	0.19	0.19	0.00	0.00	0.390	0.390	1.000$^{\varphi}$
2009-11‡	274	274	0.23	0.23	0.00	0.00	0.424	0.424	1.000$^{\varphi}$
2012-14‡	274	274	0.58	0.58	1.00	1.00	0.494	0.494	1.000$^{\varphi}$
Macro-sector:									
ICT‡	274	274	0.50	0.50	0.50	0.50	0.501	0.501	1.000$^{\varphi}$
Life Sciences‡	274	274	0.20	0.20	0.00	0.00	0.399	0.399	1.000$^{\varphi}$
Services‡	274	274	0.17	0.17	0.00	0.00	0.374	0.374	1.000$^{\varphi}$
Other‡	274	274	0.14	0.14	0.00	0.00	0.342	0.342	1.000$^{\varphi}$
Macro-region:									
DACH‡	274	274	0.28	0.28	0.00	0.00	0.452	0.452	1.000$^{\varphi}$
Nordics‡	274	274	0.12	0.12	0.00	0.00	0.322	0.322	1.000$^{\varphi}$
France & Benelux‡	274	274	0.09	0.09	0.00	0.00	0.283	0.283	1.000$^{\varphi}$
South & CESEE‡	274	274	0.06	0.06	0.00	0.00	0.242	0.242	1.000$^{\varphi}$
UK & Ireland‡	274	274	0.45	0.45	0.00	0.00	0.498	0.498	1.000$^{\varphi}$
Independence indicator									
A‡	274	274	0.15	0.10	0.00	0.00	0.361	0.303	0.073
B‡	274	274	0.31	0.32	0.00	0.00	0.465	0.469	0.784
C‡	274	274	0.01	0.01	0.00	0.00	0.104	0.104	1.000
D‡	274	274	0.34	0.42	0.00	0.00	0.473	0.495	0.035
Unknown‡	274	274	0.19	0.14	0.00	0.00	0.390	0.346	0.133
Group ownership type									
No shareholders‡	274	274	0.22	0.20	0.00	0.00	0.414	0.399	0.529
Corp. majority shareholder‡	274	274	0.57	0.57	1.00	1.00	0.496	0.496	0.931
Corp. plurality shareholders‡	274	274	0.21	0.23	0.00	0.00	0.407	0.422	0.536
Non-corp. maj./plur. sh.‡	274	274	0.00	0.00	0.00	0.00	0.060	0.000	0.318

‡ dichotomic variable; $^{\varphi}$ exactly matched.

4.2 Competing risks methods

We motivate here our choice to use competing risks methods to estimate the impact of VC on start-ups' exit outcomes and patenting. In section 2.1 we noted that, in addition to the exit route, the timing of an exit is a key element contributing to its success. For this reason, duration models — also referred to as survival models — are particularly suitable to the analysis of our data. In addition, we mentioned how VC firms can choose among several ways to divest their portfolio companies. Notably, these exit routes are mutually exclusive: this implies that we are in the presence of competing risks data.

In competing risks theory, a start-up can potentially experience one of many different exit outcomes. However, only the time-to-exit for the earliest of these is observed — or the last observed time period if no exit event has occurred yet. Until then, each exit option carries some probability to occur. The model set-up is similar in the medical literature: for instance, researchers studying mortality for a particular disease in patients may want to also account for non-disease-related deaths. In the case of venture capital investments, Giot and Schwienbacher (2007) use a competing risks framework to evaluate the incidence of various exit outcomes for VC-backed start-ups.[14]

Austin and Fine (2019) provide a useful guide to estimate treatment effects in the presence of competing risks and propensity score-matched data. The authors argue that, to estimate the relative effects of the treatment status, researchers can use the Cox (1972) model to regress the cause-specific hazard (i.e. the instantaneous rate of exiting via a given exit route) on the treatment status.[15] The estimated hazard ratios can be then used to make inference on the relative treatment effect.

In addition, researchers must also fit the data with a Fine and Gray (1999) model to estimate the absolute treatment effect, i.e. the percentage points change in the incidence of a given exit outcome due to the treatment status. In this respect, a central measure in the Fine and Gray (1999) model is the cumulative incidence function (CIF), which represents the probability that a start-up will experience a given exit outcome by a specific point in time, accounting for all other exit types. We discuss the terminology and approach of the Cox (1972) and Fine and Gray (1999) models in Appendix B.

Importantly, Austin and Fine (2019) recommend that estimates account for the matched nature of the sample by means of a cluster-robust variance estimator, where the clustering dimension is represented by the treated start-up and associated control(s). To this end, the authors recommend using the approach in Zhou *et al*. (2012), which introduces a variation of the Fine and Gray (1999) model that provides unbiased estimation of survival models in the presence of clustered data.[16]

A few recent advancements in the survival literature enhance and complete our analytical framework. Geskus (2011) proves that the Fine and Gray (1999) model can also be estimated using a weighted version of standard survival estimators for e.g., the Cox proportional hazard model. The advantage of this approach is that some of the methods developed for the Cox model can be directly applied to competing risks data (as modelled by Fine and Gray). This includes e.g., the estimation of confidence bounds for the survival/incidence curve and other auxiliary statistical tests (Lambert, 2017). In addition, Lambert (2017) discusses a series of estimators based on the Royston and Parmar (2002) flexible parametric survival model. These allow us to fit survival data and generate smooth versions of the traditional non-parametric Kaplan–Meier survival curves, which account for competing risks.

We conclude with a brief discussion of our modelling choices with respect to the treatment effect on patenting. In the case of patenting, we are able to employ a wider set of approaches other than competing risks models, since competing risks are not a prominent feature of patenting data. However, to present our results in a harmonised way, we also estimate the effect of VC on patenting under a competing risks framework. In such framework, we track start-ups over time until they apply for a patent, face bankruptcy, or become censored (i.e. all other exit outcomes are not considered). Finally, we note that while bankruptcy represents a competing event to any exit or patenting outcome, the reverse is not true: experiencing e.g., an IPO does not prevent from defaulting at a later date. Therefore, we estimate a separate model for the probability of bankruptcy, which assumes the absence of competing risks — i.e. start-ups are followed until they face bankruptcy, or become censored.

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14 However, the approach in Giot and Schwienbacher (2007) is different from the one discussed here.

15 In this setting, exit outcomes other than the one under analysis will cause censoring in the survival data.

16 Note: this option is natively available in Stata via the `vce(cluster ...)` option of the `stcrreg` routine.

5 Descriptive statistics

We present and discuss in this section a series of descriptive statistics. As shown in section 4.1, our final matched sample contains 274 VC-backed start-ups supported by the EIF as well as 274 counterfactuals that did not obtain VC financing in the years 2007-2014. We collect and assign exit outcome, bankruptcy and patenting information following the approach discussed in section 3 and Appendix A. Importantly, several data validation steps prevent us from misclassifying follow-on VC investments as exit outcomes. We obtain a quarterly panel of start-ups whose first observed period is the quarter of investment.[17] Exit outcome and bankruptcy data are censored at the first quarter of 2020, i.e. following the date of the last observed exit deal.[18] Patenting data, which tend to suffer from a longer reporting lag, are instead censored at the second quarter of 2019.

As introduced in section 2.1, we are mainly concerned with four types of competing exit events: merger and/or acquisition (M&A), initial public offering (IPO), other buy-out (e.g. institutional buy-out, management buy-in/buy-out), and bankruptcy. Start-ups in the "no exit" category do not experience any of the exit events during the observed period. Therefore, their time series become censored.

5.1 Primary exit outcomes

Table 4 provides summary statistics about the competing risks data for exit outcomes, by treatment status. The majority of start-ups across both evaluation groups did not experience an exit event. This was more often the case for counterfactual firms compared to EIF VC-backed start-ups (i.e. 51% treated and 69% controls). Among the exit events, bankruptcy was the most frequent for both groups (i.e. 24% for treated and 21% for controls). Treated firms had a slightly higher chance to experience a bankruptcy. Accounting for the sample size, however, renders this difference not statistically significant.

M&A was the second most frequent exit outcome for both treated and control firms. The finding is in line with Schwienbacher (2005), who documents the European venture firms' preference to exit via M&A. VC-backed start-ups supported by the EIF had a significantly higher chance to experience an acquisition compared to their counterfactuals. In fact, more than two thirds of all M&As in our sample were linked to VC-invested start-ups. Similarly, three times more IPOs were experienced by VC investees compared to the counterfactuals. However, the relative incidence of IPOs was rather small (i.e. 3% for treated and 1% for controls), which contributed to its weakly significant difference.[19] Other buy-outs, rarely observed, showed no tangible difference across the two groups.[20]

Table 4 also provides averages and standard deviations of the time-to-exit, i.e. the time elapsed from investment to exit date. Despite their higher likelihood to experience an exit outcome, start-ups in the treatment group generally took longer to reach a non-bankruptcy exit stage compared to counterfactuals. In particular, we observe statistically significant differences in the time-to-exit for M&A and other buy-outs. This finding is consistent with the hypothesis that VC investors actively influence

17 The first observed period of a control firm is, in fact, the investment quarter of the matched treated firm.

18 We assume that any lag in the reporting of exit and bankruptcy data is exogenous to the treatment status.

19 Specifically, significant at 90% confidence level, but non-significant at 95% confidence level.

20 As noted in Prencipe (2017), this specific exit outcome might suffer from under-reporting bias. However, we have no reason to believe that said bias should disproportionally affect either of the evaluation groups.

the timing of exit events to maximise their returns (Bergemann *et al.*, 2008; Li *et al.*, 2016).[21] We also note the absence of statistically significant differences in the timing of IPOs as well as of bankruptcies.

Table 4: Distribution of primary exit outcomes, by treatment status

Treatment status	No exit	M&A		IPO		Other Buy-out		Bankruptcy		Total
	Number (%)†	Number (%)†	TTE‡ avg (sd)	Number (%)†	TTE‡ avg (sd)	Number (%)†	TTE‡ avg (sd)	Number (%)†	TTE‡ avg (sd)	Number (%)†
VC-invested	139 (50.7%)	56 (20.4%)	4.5 (2.3)	9 (3.3%)	4.1 (3)	4 (1.5%)	6.2 (2.6)	66 (24.1%)	4.6 (2.5)	274 (100%)
Counterfactuals	189 (69%)	19 (6.9%)	3 (2)	3 (1.1%)	2.9 (2.5)	5 (1.8%)	3.4 (1.7)	58 (21.2%)	4.8 (2.9)	274 (100%)
Total	328 (59.9%)	75 (13.7%)	4.1 (2.3)	12 (2.2%)	3.8 (2.8)	9 (1.6%)	4.6 (2.5)	124 (22.6%)	4.7 (2.7)	548 (100%)

† **Note:** numbers and percentages sum up horizontally (aggregates are in the Total column). ‡ TTE: time-to-exit (in years).

5.2 Secondary M&A outcomes

The predominance of M&A among the exit outcomes of EIF VC-invested start-ups motivates us to undertake an in-depth analysis of this exit event, which we briefly describe here. Table 5 breaks down the M&As in our sample by treatment status and the nature of the M&A. We follow the methodology in Alfaro and Charlton (2009) and classify them into vertical or horizontal integrations or diversifications based on the relationship between the start-up's and the acquiror's industries.[22] Moreover, we compare the headquarters' location of the start-up and the acquiror(s) to differentiate between national, international and intercontinental (i.e. extra-EU) mergers and acquisitions.

Statistical tests on the summary data in Table 5 show that EIF-supported VC significantly increased the likelihood to be involved in acquisitions pursuing either horizontal or vertical synergies. By contrast, the likelihood to be acquired in a diversification was not significantly affected. As per the geographical dimension of M&As, we find that VC-invested start-ups are significantly more likely to experience international acquisitions, either by acquirors in the EU or the UK, or located outside of the EU. The rate of domestic acquisitions shows no statistically significant differences across the two groups.

Table 5: Distribution of merger and/or acquisition (M&A) outcomes, by treatment status

Treatment status	M&A integration type			Location of M&A buyer(s)‡		
	Horizontal (Nr/%)†	Vertical (Nr/%)†	Diversified (Nr/%)†	National (Nr/%)†	EU or UK (Nr/%)†	Extra-EU (Nr/%)†
VC-Invested	24 (8.8%)	23 (8.4%)	9 (3.3%)	18 (6.6%)	14 (5.1%)	24 (8.8%)
Counterfactuals	7 (2.6%)	4 (1.5%)	8 (2.9%)	13 (4.7%)	1 (0.4%)	5 (1.8%)
Total	31 (5.7%)	27 (4.9%)	17 (3.1%)	31 (5.7%)	15 (2.7%)	29 (5.3%)

† Figures sum up horizontally. ‡ In case of multiple buyers, we classify deals with at least one foreign buyer as non-national M&A. Most deals with a foreign buyer have exclusively non-national buyers.

21 Exit returns are beyond the scope of this work, so we cannot provide conclusive evidence in this regard.

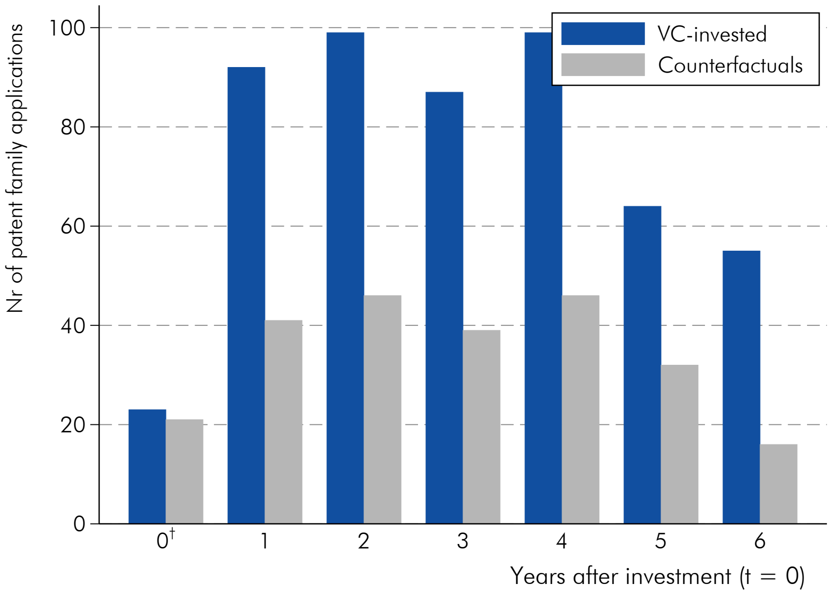
22 The relationship is based on input-output tables for the EU27 and the UK at the NACE Rev. 2 division level. For horizontal integrations, the acquiror's and the target's primary and secondary NACE Rev. 2 divisions must coincide. Two given NACE industries are considered vertically integrated if the first's input to the latter represents at least 5% of the latter's output. Otherwise, we consider the acquisition a diversification. Mixed horizontal/vertical integrations are assigned according to the start-up's primary NACE Rev. 2 division and, in case of residual uncertainty, we default to consider them vertical integrations.

5.3 Patenting activity

We now turn to the innovative activity of VC-invested start-ups and associated counterfactuals, as measured through patent data.[23] Overall, 132 companies (out of 548) recorded any patenting activity in the years following the VC investment. Of these, 84 were in the treatment group and 49 in the control group. In other words, VC-backed companies had a significantly higher chance (31%) to apply for a patent compared to their counterfactuals (18%) in the years following a VC investment.

In Figure 2, we plot the number of patent applications for the two start-up groups, by post-investment year. The plot confirms that VC-invested start-ups patent at a higher rate than their controls. Note that due to the censored nature of our data, the falling number of innovations over time does not necessarily reflect a decline in patenting, but rather a shrinkage of the sample with observable data.[24]

Figure 2: Aggregate patenting activity, by treatment status



† Patenting activity at investment year is comparable by construction (see section 4.1). We assume that VC firms can detect the presence of patentable technologies prior to the time of the investment: as such, patent applications submitted in the investment year are considered to be factored in the appraisal process. See also Pavlova and Signore (2019).

6 Competing risks analysis

We discuss here our estimates for the relative and absolute effect of VC on the exit and patenting outcomes of start-ups supported by the EIF. In line with Austin and Fine (2019), we first estimate the relative treatment effect via a series of outcome-specific Cox proportional hazard regressions (Cox, 1972). Second, we estimate the absolute treatment effect, i.e. the absolute percentage point (pp) change in the incidence of a given outcome due to the treatment status, via the Fine and Gray (1999) model.

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[23] See section 3 for details about the data collection process and our choice of innovation measure.

[24] There are more observable periods for firms invested in, say, 2007 than for those invested in 2014.

According to Austin and Fine (2019), in the presence of matched samples, it is sufficient to compute the difference of the two groups' cumulative incidence functions (CIFs) to measure the treatment effect. This seemingly contradicts the often favoured strategy in the evaluation literature to adjust for residual covariate imbalance after matching with the propensity score. However, one important consideration that supports this approach is that to correctly fit survival models, a minimum of 5 to 9 exit events per covariate are necessary to avoid e.g., bias, variability, and over-fitting (Vittinghoff and McCulloch, 2007). Table 4 above certifies this concern for a few of the exit events under scrutiny.

Against this backdrop, for each exit outcome we evaluate two separate model specifications. The first one is a univariate, unadjusted regression of the exit outcome's incidence on the treatment status. This first specification constitutes our baseline result, as per the aforementioned considerations. It is also the basis for our estimation of the cumulative incidence functions — see further below.

The second specification includes a few additional controls, sourced from the list of determinants and predictors of VC financing (see section 4.1). This specification ought to test whether the treatment effect is sensitive to any residual imbalance in the two matched samples. Moreover, it offers some insights on the mechanism underlying the occurrence of a given exit outcome. For instance, we find that start-ups were more likely to go public if they had applied for a patent at investment date, while they were less likely to go bankrupt the higher their degree of innovativeness (regardless of their treatment status).

6.1 Primary exit outcomes

Table 6 shows the estimated coefficients for the relative impact of EIF VC, based on Cox regressions for the four competing exit outcomes of section 5.1. Table 6 provides the Odds Ratios (ORs) for a given exit outcome. As already mentioned in section 4.1, an OR > 1 implies that the exposure is associated with increased odds to observe the outcome, while OR < 1 implies the opposite.

Column 1 of Table 6 shows that EIF VC had a strong and positive effect on the likelihood of experiencing an acquisition. We find that EIF VC-invested start-ups were about three times more likely to participate in an M&A deal than their non-VC invested counterfactuals. The result is significant at the 99.9% confidence level, offering strong evidence that venture capital investments contributed to the occurrence of this exit route. In addition, Column 2 of Table 6 shows that the magnitude and significance of this result hold even after controlling for residual covariate imbalance.

Given that M&As are an important value-generating channel for VC firms (Hochberg *et al.*, 2007),[25] we expect EIF-backed VC to have significantly raised the net gains of investors and entrepreneurs — as also addressed in our previous work (Pavlova and Signore, 2019) from the entrepreneurial side.

In columns 3 and 4 of Table 6, we estimate the relative effect of VC on the likelihood to experience an IPO. The magnitude of our estimated odds ratios is similar to the case of M&As and robust to further covariate adjustments. Moreover, it is consistent with our summary statistics in section 5.1, i.e. start-ups backed by EIF VC were roughly three times as likely to go public than the controls.

25 Hochberg *et al.* (2007) estimate that a 2.5 percentage points increase in M&A and/or IPO exit rates is linked to approximately a 2.5 percentage point increase in the internal rate of return (IRR) of the VC fund.

Table 6: Primary outcomes: estimated odds ratios for the Cox proportional hazard model (PHM)

	M&A		IPO		Other Buy-out		Bankruptcy$^{\alpha}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PHM	PHM	PHM	PHM	PHM	PHM	PHM	PHM
VC-invested	3.220***	2.934***	3.254†	3.327†	0.891	1.001	1.183	1.266
	(0.849)	(0.796)	(2.207)	(2.385)	(0.544)	(0.655)	(0.185)	(0.219)
Firm age at inv. year		1.058		0.995		0.921		0.994
		(0.070)		(0.153)		(0.155)		(0.048)
Predicted degree of innovativ.		1.061		3.184		0.463		0.408***
		(0.344)		(2.918)		(0.448)		(0.086)
Patent at inv. year		0.583		4.062*		1.950		0.989
		(0.222)		(2.789)		(2.461)		(0.217)
Propensity score		4.930*		1.412		0.036		0.579
		(3.448)		(1.955)		(0.075)		(0.301)
Corp. group covariates‡	No	Yes	No	Yes	No	Yes	No	Yes
Log-Likelihood	-434.94	-411.97	-69.28	-64.01	-52.84	-48.39	-809.22	-790.81
N° of observations	548	548	548	548	548	548	548	548
N° of exit events	75	75	12	12	9	9	137	137
Tot. time at risk (quarters)	14,351	14,351	14,351	14,351	14,351	14,351	15,835	15,835

† 0.10 * 0.05 ** 0.01 *** 0.001; ‡ n° of shareholders, Independence indicator; cluster-robust std errors in brackets.

$^{\alpha}$ Estimated under the assumption of no competing risks (see section 4.2). This explains the sample size discrepancy with Table 4.

However, this result is only weakly significant: we speculate that this is not necessarily driven by the lack of significant differences between the outcome propensities of the two groups, but by the matched sample's size and its relative lack of IPOs. In fact, the analysis of the statistical power of these models shows that their significance tests are underpowered for e.g., a confidence level of 95%.[26]

Another indication towards the plausibility of our hypothesis can be found in Appendix C. There, we use of more lenient matching techniques, which lead to larger matched samples — these are expected to yield less consistent estimates, albeit more efficient (Caliendo and Kopeinig, 2008). Given the larger sample sizes in these auxiliary analyses — as well as higher point estimates for the treatment effect — we consistently obtain a strongly significant and positive impact of VC investments on the probability to IPO.

Columns 5 and 6 of Table 6 present our estimates for the case of other buy-outs. Analogously to the case of IPO data, the regressions' low statistical power constitute an important caveat. Nevertheless, for this exit route, our estimates fail to provide any direction on whether the effect of EIF VC might be either positive or negative. Thus, for the case of other buy-outs, our results are inconclusive at best.

Lastly, columns 7 and 8 of Table 6 provide estimates on the impact of EIF VC on the likelihood to default. As discussed in section 4.2, we estimate the effect of VC on start-ups' bankruptcy rates under the assumption of no competing risks. This is because e.g., an IPO does not necessarily prevent a start-up from defaulting at a later time. Hence, for this specific regression we can use an expanded version of our dataset, which does not censor firms that face an exit route other than bankruptcy.

Columns 7 and 8 show that the difference in the bankruptcy rates between the two groups is not significant. Contrary to our regressions on IPOs and other buy-outs, we observe a sizeable number of bankruptcies across the two groups. Unfortunately, we find that this is still not sufficient to confirm the lack of statistical significance for the estimated effect. While our analysis is underpowered and

[26] Given our sample size, $\alpha = 0.05$, $(1-\beta) = 0.8$, the observed IPO probability and standard deviation of the treatment effect, we find that the lowest odds ratio detectable by these models is OR ≈ 4.2.

cannot determine whether the observed difference between the two groups' bankruptcy rates is truly non-significant, we are still able to speculate that the magnitude of this effect, if at all confirmed, is likely much more contained than e.g., the observed effects on M&As and/or IPOs.[27]

We now turn to the analysis of the absolute treatment effect of EIF VC. Figure 3 plots the cumulative incidence function in the presence of competing risks, separately by exit route and treatment status. As mentioned above, each plot is based on the unadjusted regression of the exit outcome's incidence on the treatment status (i.e. the models in columns 1, 3, 5 and 7 of Table 6). Appendix D provides alternative (but consistent) results from our other model specifications. In Figure 3, the dashed lines portray the non-parametric estimates of the CIF based on the Fine and Gray (1999) model. On top of these, we add a smooth parametric CIF and its 95% confidence band, as in Lambert (2017).

Figure 3: Changes in the CIF due to treatment, by exit route

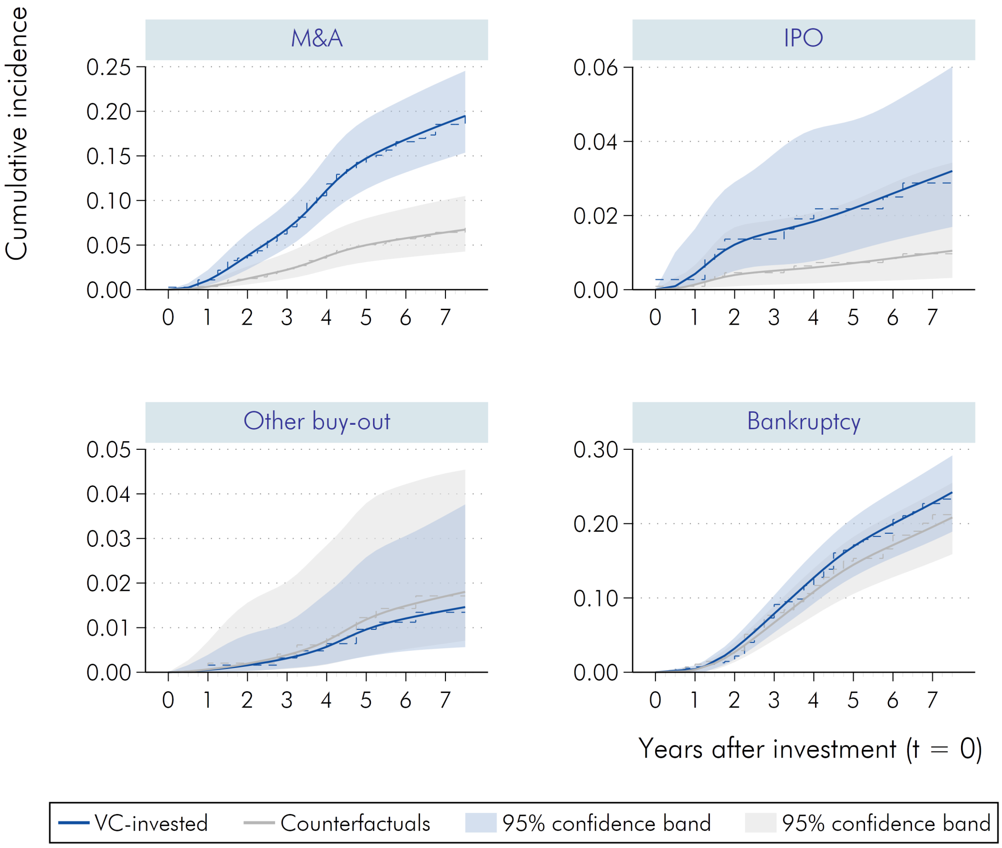


Figure 3 provides complementary insights to the findings of our Cox proportional hazard regressions. The significant and positive effect of EIF VC on the probability to be acquired translates into a 10.3 pp higher CIF for treated start-ups five and a half years after the investment date. According to Figure 3, the two incidence functions start diverging significantly between the third and fourth post-investment years. This clarifies the time-to-event descriptives observed in section 5.1.

With regard to IPOs, Figure 3 confirms the estimates from Table 6. That is, the CIF for treated start-ups is 1.9 pp higher than the counterfactuals, starting from six and a half years after the investment date (1.7 pp higher after five and a half years). Figure 3 also confirms that the confidence bands for

[27] Given our data setting, this test would have had a 95% chance of identifying a statistically significant difference at 95% confidence level had we observed an OR ≥ 1.85 (or an OR ≤ 0.54).

the two CIFs overlap at the 95% confidence level. Finally, Figure 3 reinforces the lack of significant deviations for the CIFs of other buy-outs and bankruptcies. As mentioned above, however, the last two results might be inconclusive given the low power of our statistical tests.

6.2 Secondary M&A outcomes

This section provides competing risks estimates for the various types of M&A presented in section 5.2. Table 7 shows that EIF VC had a strong and significant effect on the likelihood to experience both a horizontal and vertical integration, with a threefold and sixfold increase in the probability of each M&A outcome respectively. In absolute terms, Figure 4a shows that both outcomes have a 5 pp higher incidence for EIF-backed start-ups by the fifth post-investment year. By contrast, the effect of EIF VC on M&A deals representing a diversification is not apparent. As such, our tests are unable to determine whether the two groups experience significantly different rates of exit via diversification.

Table 8 presents the effect of EIF VC differentiating by the headquarters' location of M&A buyers. We find that EIF VC led to an almost sixfold increase in the likelihood of experiencing international acquisitions (columns 1 and 2 of Table 8). EIF VC had a much more muted effect on the likelihood to experience national integrations (columns 3 and 4 of Table 8), so that our tests are unable to detect any significant difference between the two groups. Figure 4b documents the strong absolute treatment effect on the probability of foreign acquisition, with EIF-backed start-ups showing an 8 pp higher incidence of M&As with at least one foreign buyer, by the fifth post-investment year.

Table 7: M&A integrations: estimated odds ratios for the Cox proportional hazard model (PHM)

	Horizontal integration		Vertical integration		Diversification	
	(1)	(2)	(3)	(4)	(5)	(6)
	PHM	PHM	PHM	PHM	PHM	PHM
VC-invested	3.779**	3.329**	6.259***	6.150***	1.217	1.157
	(1.568)	(1.494)	(3.339)	(3.387)	(0.606)	(0.602)
Firm age at inv. year		1.185†		0.815		1.161†
		(0.113)		(0.106)		(0.104)
Predicted degree of innovativ.		0.669		3.733†		0.575
		(0.315)		(2.642)		(0.372)
Patent at inv. year		0.078*		0.781		1.926
		(0.078)		(0.465)		(1.030)
Propensity score		12.161*		3.245		2.849
		(13.110)		(3.176)		(4.124)
Corp. group covariates‡	No	Yes	No	Yes	No	Yes
Log-Likelihood	-179.26	-165.24	-151.80	-141.75	-101.04	-92.75
N° of observations	548	548	548	548	548	548
N° of exit events	31	31	27	27	17	17
Tot. time at risk (quarters)	14,351	14,351	14,351	14,351	14,351	14,351

† 0.10 * 0.05 ** 0.01 *** 0.001; ‡ n° of shareholders, Independence indicator; cluster-robust std errors in brackets.

These findings help us speculating about the mechanism underlying the EIF-backed start-ups' higher chance of experiencing an acquisition. The presence of VC investors could open up additional exit channels for receiving start-ups, which would not otherwise be available to entrepreneurs. In our sample, this translated into a disproportionally positive impact on horizontal and vertical integrations.[28]

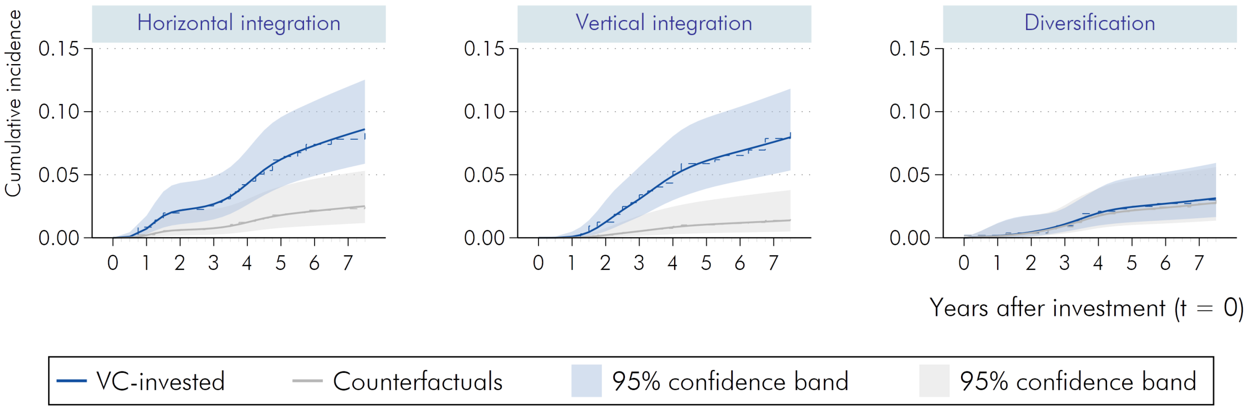
[28] See Achleitner *et al.* (2012) for implications in terms of VC returns. Note, however, that the authors' alternative classification method might explain their higher rate of diversifications compared to our study.

Table 8: M&A buyer(s) types: estimated odds ratios for the Cox proportional hazard model (PHM)

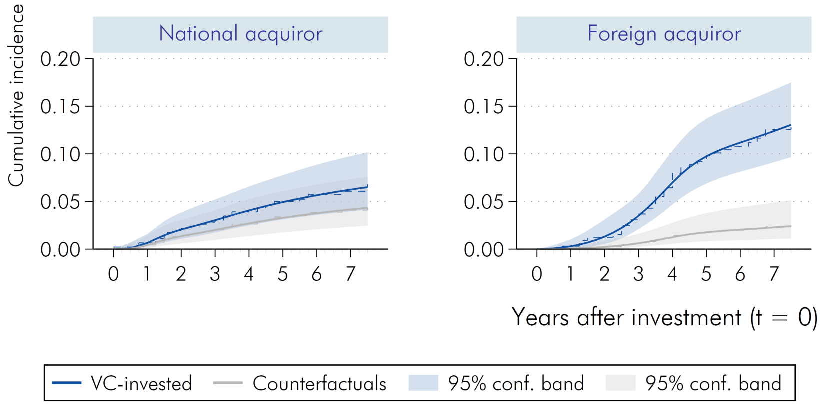
	Foreign		National	
	(1)	(2)	(3)	(4)
	PHM	PHM	PHM	PHM
VC-invested	5.995***	5.456***	1.612	1.634
	(2.418)	(2.432)	(0.621)	(0.656)
Firm age at inv. year		1.037		1.109
		(0.092)		(0.088)
Predicted degree of innovativ.		1.231		0.964
		(0.509)		(0.494)
Patent at inv. year		0.320*		1.146
		(0.176)		(0.548)
Propensity score		9.703**		1.653
		(8.160)		(1.849)
Corp. group covariates‡	No	Yes	No	Yes
Log-Likelihood	-252.97	-238.82	-179.05	-168.35
N° of observations	548	548	548	548
N° of exit events	45	45	30	30
Tot. time at risk (quarters)	14,351	14,351	14,351	14,351

† 0.10 * 0.05 ** 0.01 *** 0.001; ‡ n° of shareholders, Independence indicator; cluster-robust std errors in brackets.

Figure 4: M&A outcomes: changes in the CIF due to treatment, by M&A route



(a) M&A integration type



(b) Location of M&A buyer(s)

Moreover, as shown in the literature (Bertoni and Groh, 2014), this effect might be further amplified by the presence of numerous cross-border investments in our sample (see Kraemer-Eis *et al.*, 2016). In turn, the significant share of cross-border investments might explain the disproportionally positive impact on the likelihood to experience M&A with at least one foreign buyer.

An alternative theory is that this phenomenon could be entirely driven by the higher post-investment financial growth caused by the VC investment (as documented in our previous work). In turn, this would increase the likelihood of experiencing positive exit outcomes. While our empirical approach cannot isolate the effect of VC on exit outcomes from its effect on financial growth, we note that if the hypothesis of a purely growth-driven effect were true, it would be harder to explain why EIF VC disproportionally affected some types of integrations and not others.

6.3 Patenting activity

As discussed in section 4.2, there are several strategies to measure the impact of VC on innovation. We discuss here the results of a competing risks analysis, so as to provide estimates consistent with the previous sections. Interested readers can refer to Appendix E, which discusses a standard least squares approach that nevertheless delivers comparable results. In this setting, bankruptcy and innovation are the relevant competing risks, so we disregard the other exit outcomes. In other words, we track start-ups until they apply (and/or acquire patenting rights)[29] for an innovation, face bankruptcy, or neither.

Table 9 and Figure 5 report our results. We see a significant positive effect of EIF VC on patenting activity — implying that VC-invested companies innovate at a significantly higher rate than their counterfactuals. Table 9 points to a doubling in the likelihood to patent for start-ups backed by EIF VC compared to their counterfactuals. Figure 5 shows a 10 pp difference in the incidence to patent between the two groups, already by the second post-investment year — this goes up to 13 pp by the sixth year after investment. These results are consistent with the descriptive evidence presented in section 5.3 and support the "VC-first" hypothesis discussed in section 2.2. That is, VC firms play a significant role in fostering the innovative capacity of start-ups.

Bertoni *et al.* (2010) summarise the potential mechanism through which VC firms can stimulate the innovation performance of portfolio companies. Firstly, VC provides the necessary means for financially-constrained firms to support R&D as well as to cover the direct and indirect costs of patenting. Secondly, VC investors actively monitor the behaviour of investees and also put in place specific financial instruments and contractual clauses creating high-powered incentives for the entrepreneurs. This tighter discipline results in greater innovation productivity. In addition, such monitoring might prove a direct incentive towards patenting, whether formally (i.e. through agreed milestones) or informally (i.e. as a signal to investors). By contrast, non-VC-backed firms might face a less stringent governance. In turn, this might lead to, ceteris paribus, diverging incentives towards patenting.

Bertoni *et al.* (2010) also suggest that start-ups receive valuable advisory services from VC firms in

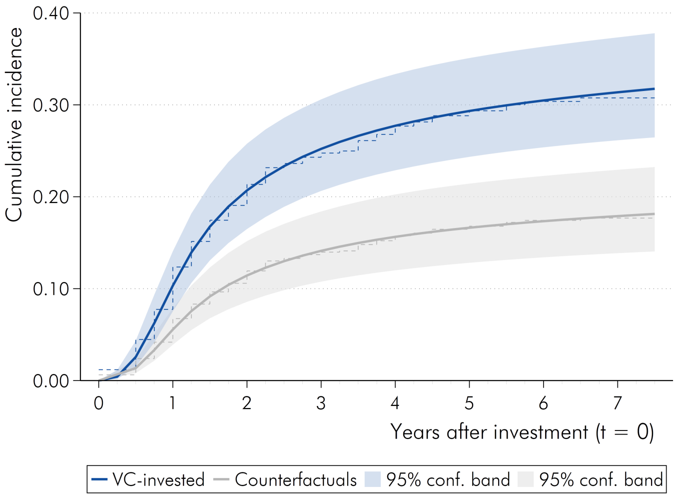
[29] As mentioned in footnote 9, the bulk of our patent applications data consists of innovations internally developed by the firm — as opposed to innovation rights acquired externally.

Table 9: Patenting activity: estimated odds ratios for the Cox proportional hazard model (PHM)

	Patenting	
	(1)	(2)
	PHM	PHM
VC-invested	1.901***	2.172***
	(0.261)	(0.349)
Firm age at inv. year		0.927
		(0.046)
Predicted degree of innovativ.		1.914*
		(0.506)
Patent at inv. year		7.275***
		(1.699)
Propensity score		2.105†
		(0.924)
Corp. group covariates‡	No	Yes
Log-Likelihood	-805.06	-727.82
N° of observations	548	548
N° of exit events	133	133
Tot. time at risk (quarters)	11,378	11,378

† 0.10 * 0.05 ** 0.01 *** 0.001; ‡ n° of shareholders, Independence indicator; cluster-robust std errors in brackets.

Figure 5: Changes in the CIF for patenting due to treatment



areas where they might lack internal capabilities. Furthermore, investees can also take advantage of their VC investors' wide network of contacts. Therefore, the authors conclude that the resource and competence endowment that VC-backed start-ups can rely on substantially exceeds the one of their non-VC-backed counterparts. In turn, this leads to greater R&D investments and innovation output.

6.4 Moderating effects

The purpose of this section is to discuss whether start-up characteristics shape the direction and size of the estimated effects. Our main econometric tool is the test in Gray (1988), providing a version of the log-rank test for competing risks data.[30] A log-rank test compares the observed number of

[30] To prevent e.g., over-fitting and variability (as mentioned at the beginning of section 6), we avoid the standard approach to augment our baseline model with multiple interaction terms. When the sample size allows, however, this alternative strategy's results are consistent with the ones discussed in this section.

outcomes in each group against an expected number of outcomes, each time an event occurs. The expected number is calculated based on the assumption of no difference between the groups, i.e. the two groups are both subject to the outcome hazard rate observed in the full sample.

Notably, the log-rank statistic can only test whether the difference between the survival/duration curves of two groups is statistically significant, but it cannot quantify said difference without further assumptions (e.g. those of the Cox model). We can, however, qualitatively describe the effect's direction by comparing the observed and expected number of events, as we do in Table 10. Table 10 provides, for each exit route and moderating variable, the ratio of observed *vs* expected events, and the associated log-rank test statistic information. A ratio above (below) 1 points to a positive (negative) effect.

Our findings do not support the argument that the effects of EIF VC are highly heterogeneous. In fact, Table 10 demonstrates that the main effects measured in sections 6.1 and 6.3 broadly apply to the numerous sub-samples defined by each moderating variable.[31] Most often, the presence of statistically significant differences between the exit duration curves boils down to the larger sizes of a few groupings, rather than the actual larger/smaller estimated effect of EIF VC in the sub-samples.

Table 10 also points to a few instances where the main effect might be driven by a specific sub-sample in the data. For instance, the effect of EIF VC on IPO rates seems mostly driven by life sciences start-ups as well as start-ups with a high degree of innovativeness. Nevertheless, we conclude that the characteristics of start-ups do not meaningfully shape the direction and size of the estimated effects.

6.5 Robustness checks

We conclude the analysis of the results with a discussion on the robustness of our baseline estimates. We provide here a summary of Appendices C and E, which contain in-depth information about several robustness checks meant to evaluate the sensitivity of our empirical setting to various biases.

The first common concern with causal inference studies is the issue of omitted variable bias (OVB). Put simply, OVB stems from the failure to account for features that influence the treatment assignment. This could lead to the treatment effect be owed in part, or worse, fully, to the omitted variable(s). For example, if we had failed to account for start-up and/or founder attributes influencing the company's likelihood to obtain VC, our estimated difference between treated and control firms might be biased.

One strategy to address this issue is Rosenbaum's sensitivity analysis (Rosenbaum, 2005). Rosenbaum's test reports the significance level of the estimated treatment effect under varying degrees of assumed hidden bias. In turn, this informs us about the maximum level of bias that would still allow for our treatment effects' significance to hold.

The sensitivity analysis results reveal overall robustness to hidden biases. VC-invested firms would still have a significantly higher chance to experience an M&A deal even if they were more than twice as likely to receive VC than the counterfactuals, due to hidden biases. The effect of EIF VC on patenting is similarly robust: it would remain significant even if treated firms were 40% more likely to be treated.

[31] There are only a handful of exceptions, none of which are statistically significant.

Table 10: Observed *vs* expected events ratio and log-rank test for treated firms, by moderator.

	M&A	IPO	Other Buy-out	Bankruptcy	Patenting
	(1)	(2)	(3)	(4)	(5)
	LOG-RANK	LOG-RANK	LOG-RANK	LOG-RANK	LOG-RANK
Investment period:					
2007-08	1.770**	1.005	1.010	0.889	1.439**
	(7.802)	(0.000)	(0.000)	(0.433)	(7.237)
2009-11	1.449†	2.020	1.000	1.216	1.509**
	(3.795)	(2.055)	(0.000)	(1.549)	(6.855)
2012-14	1.497**	1.678†	0.800	1.121	1.217
	(9.747)	(2.714)	(0.203)	(1.018)	(2.608)
Macro-sector:					
ICT	1.746***	0.000	0.500	1.089	1.569**
	(24.601)	(2.007)	(1.008)	(0.479)	(10.047)
Life Sciences	1.200	1.775*	1.887	0.738	1.354**
	(0.404)	(3.923)	(0.898)	(1.565)	(7.217)
Services	1.121	1.961	0.000	1.144	1.154
	(0.128)	(1.921)	(2.022)	(0.767)	(0.370)
Other	1.272	2.083	2.020	1.365	1.291
	(0.580)	(1.093)	(2.057)	(2.314)	(1.123)
Predicted degree of innovativ.:$^{\times}$					
Below 30%	1.506*	1.000	0.797	0.985	1.330†
	(6.291)	(0.000)	(0.206)	(0.017)	(2.896)
Between 30% and 70%	0.938	–$^{\varphi}$	0.000	0.942	1.433
	(0.026)		(1.042)	(0.054)	(1.315)
Above 70%	1.628***	1.610†	1.299	1.235†	1.331**
	(16.116)	(3.683)	(0.285)	(2.816)	(9.668)
Firm age at inv. year:$^{\times}$					
Less than 2 yrs	1.696***	1.661	1.181	1.104	1.235*
	(22.185)	(2.642)	(0.169)	(0.917)	(4.415)
2 to 5 yrs	1.190	1.606	0.498	1.009	1.546**
	(0.741)	(1.831)	(1.025)	(0.003)	(9.802)
5 or more yrs	1.481	0.000	–$^{\varphi}$	1.215	1.308
	(1.166)	(1.048)		(0.459)	(1.002)
Macro-region:					
DACH	1.912***	–$^{\varphi}$	1.307	1.433	1.739***
	(16.762)		(0.293)	(2.287)	(13.165)
Nordics	1.170	1.195	0.000	0.995	1.429†
	(0.303)	(0.193)	(1.000)	(0.000)	(3.689)
France & Benelux	1.471	2.041†	2.000	1.343	1.127
	(1.477)	(3.133)	(1.000)	(1.528)	(0.200)
South & CESEE	2.066*	1.887	0.000	0.713	1.445
	(5.354)	(0.873)	(1.000)	(0.982)	(1.370)
UK & Ireland	1.297†	1.325	0.662	1.047	1.148
	(2.720)	(0.321)	(0.342)	(0.208)	(1.317)
N° of observations	548	548	548	548	548
N° of exit events	75	12	9	137	133
Tot. time at risk (quarters)	14,351	14,351	14,351	15,835	11,378

† 0.10 * 0.05 ** 0.01 *** 0.001; log-rank χ^2-statistic in brackets; $^{\varphi}$ no exit events in the respective sub-sample;
$^{\times}$ For more information on the selection of these thresholds, please refer to section 4.3 in Pavlova and Signore (2019).

Secondly, we construct two alternative models to corroborate our main results. In the case of exit outcomes, we replace the Fine and Gray (1999) model with a discrete-time multinomial logit competing risks model. This allows us to test whether our results are sensitive to the continuous time assumption made in Fine and Gray (1999). In the case of patenting, we also provide estimates for the average treatment effect (ATT) from a standard least squares regression, in line with our previous work (Pavlova and Signore, 2019). As discussed in section 4.2, this modelling choice is suitable, and arguably preferable, in the case of patent count data.

The multinomial logit model yields estimates that are very close in both magnitude and significance to our baseline results. The least squares regression also confirms that VC-invested firms generate significantly more patent applications and/or acquisitions. Overall, the two alternative modelling strategies provide full support to our baseline estimates.

In Appendix C, we check whether alternative matching strategies would yield different estimates. In addition to our baseline estimator, based on a 1:1 nearest neighbour (NN) matching with calliper equal to the standard deviation of the treatment group's propensity score, we carry out and describe two estimators based on alternative matching approaches.

The first estimator is based on a 1:1 NN matching without calliper — each treated firm is matched to the control with the closest propensity score, without constraining how far away said score might be. The second estimator is a 3:1 NN matching with calliper. According to Caliendo and Kopeinig (2008), these alternative estimators should yield less consistent estimates, albeit more efficient.

The results on the M&A exit type remain positive and significant irrespective of the implemented matching. Interestingly, our baseline result lies between the estimates of the two additional matching strategies in terms of magnitude. As indicated in section 6.1, under these alternative specifications, the effect of EIF VC on IPO rates becomes significant at the 95% and 99% confidence levels. That is, EIF VC-invested start-ups are significantly more likely to experience an IPO.

The treatment dummy coefficients on Other Buy-outs remain non-significant when estimated on the two alternative samples. Equally non-significant remains the effect of EIF VC on start-ups' bankruptcy rates. Finally, irrespective of the matching design, VC-invested companies innovate significantly more than their counterfactuals: the estimates' magnitude is similar across the different matching strategies.

7 Concluding remarks

No two traits are perhaps more representative of the VC industry than exit outcomes and innovation. They capture the essence of VC investing — to finance innovative business ideas for a profit, via well-timed exit events. Importantly, these two phenomena tend to generate spillovers. In turn, this explains the attention of governments towards the VC industry and tends to guide the latter's policy actions.

Bertoni *et al.* (2011) show that 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. Phillips and Zhdanov (2017) show that an active M&A market provides an incentive for VC firms to engage in more VC deals, supporting the hypothesis that a virtuous cycle exists between VC activity, the exit environment and innovation spillovers.

Against this backdrop, the contribution of this paper is twofold. First, we present compelling evidence that EIF VC effectively raised start-ups' chances to experience exit outcomes known to be remunerative for VC firms (Achleitner *et al.*, 2012). In particular, we find a strong and significant effect of EIF VC in the case of M&A and a similarly strong albeit weakly significant effect in the case of IPOs. Second, we provide compelling evidence that EIF VC positively impacted the innovation capacity of beneficiary start-ups, as measured via their patenting activity.

As with most empirical works, our research entails some limitations. We discuss and address many of these in section 6.5, where we find that our main results are generally robust to multiple potential sources of bias. Furthermore, in section 3 we discuss how our empirical strategy can only identify the cumulated effect of a VC investment and the contribution brought by the presence of the EIF in said VC investment. Additional research will be necessary to isolate the differential effect directly attributable to the presence of the EIF in a given VC investment.

Overall, our work provides meaningful evidence towards the positive effects of EIF-supported VC investments on the exit prospects and innovative capacity of young and innovative businesses in Europe. In addition, it provides supplemental evidence to our previous work (Pavlova and Signore, 2019), which showed that EIF VC significantly contributed to the financial growth of receiving start-ups. Taken together, these findings point to the effectiveness of EIF's policy instruments supporting SMEs' access to VC financing in Europe, in line with the existing economic literature.

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Appendices

A Identification and compilation of exit outcomes data

The process to identify and assign exit outcomes to treated and control firms is based on the tracking of legal entities within corporate groups. In this setting, a legal entity is a synonym for any private limited company. Corporate groups are collections of legal entities characterised by an ownership chain. If the company does not have any recorded shareholder, the legal entity and the corporate group coincide, as it is the case for about 30% of our sample.

Our initial dataset contains 782 legal entity codes for start-ups backed by EIF VC and 53,761 codes for candidate control start-ups that did not receive VC financing. Legal entity codes for start-ups backed by EIF VC were retrieved based on e.g., the name, country, date of establishment, industry of the start-up. To ease data processing, our starting 53,761 candidate controls already match the treatment group in terms of geography, industry, age, patent ownership and degree of innovativeness (i.e. the discriminants of VC financing, see section 4.1).

As stated in section 3, exit deals are collected from Bureau Van Dijk's Zephyr database. We assign an exit deal to a given start-up if: a) the legal entity code of the start-up is reported in the deal description; b) the legal entity code of any start-up's shareholder with 50% or higher ownership stake (either directly or indirectly) is reported in the deal description.

We identify the start-ups' shareholders in each year starting from the year of investment, so as to account for the dynamic nature of corporate groups. We impute missing participation shares assuming a "missing completely at random" pattern. This entails a re-allocation of missing participation shares among the observed shareholders, proportionally.[32] Overall, we analyse 297,349 corporate group configurations, with an average number of 40 entities and a median of 3.

We use network theory to identify and evaluate all direct and indirect ownership paths between any two given entities (nodes) in a corporate group (network). To limit the computational burden, we implement a number of simplifying assumptions, particularly necessary for large corporate groups: a) we only look at (indirect) ownership paths of 5 steps or fewer; b) for corporate groups with 99 to 399 entities, we remove all network edges representing a participation rate of 5% or lower; c) for corporate groups with more than 399 entities, we use the algorithm in Blondel *et al.* (2008) to identify the closest cluster of shareholders for a given legal entity, and proceed to identify ownership paths on such restricted partition. The output of this exercise is an additional list of 19,521 legal entities that are direct or indirect owners of either treated or control firms. Should these legal entities experience an exit outcome, this would be assigned to the associated treated/control firm as well.

We identify 6,032 exit deals, with 27% assigned directly to the start-ups' legal entities and 73% assigned to their shareholders. We undertake significant data cleaning to ensure that the identified deals are valid exit outcomes for the associated start-up. To this end, we discard more than half of the identified exit deals on the account of: a) the deal being prior to the window of interest (i.e. the start-

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[32] For instance, if the recorded shareholders make up only 80% of the ownership of a given start-up, each owner's participation share is multiplied by 1.25 so as to bring the total observed ownership to 100%.

up's post-investment period); b) the start-up not being directly/indirectly owned by the shareholder at the time of the shareholder's exit deal; c) missing corporate group information at the time and/or prior to the shareholder's exit deal. We obtain a final count of 2,760 exit events, half of which pertain to the start-ups' legal entities and the other half to their shareholders'.

The classification of exit events is principally based on the deal descriptions of the Zephyr database. However, we undertake additional data cleaning to ensure consistency. For instance, all M&As with a buyer(s) that is (are) identified as VC firm(s) are automatically converted into institutional buy-outs (hence, added to the other buy-outs category), unless the deal happened in the same year as the recorded investment date — in which case, we assume the deal corresponds to the EIF-backed VC investment and discard it altogether from the analysis.

We further partition M&As into vertical or horizontal integrations or diversifications, based on the methodology in Alfaro and Charlton (2009). The approach is centred on the relationship between the start-up's and the acquiror's industries. In turn, this is based on input-output tables for the EU27 and the UK at the NACE Rev. 2 division level. For horizontal integrations, the acquiror and the target's primary and secondary NACE Rev. 2 divisions must coincide. Two given NACE industries are considered vertically integrated if the first's input to the latter represents at least 5% of the latter's output. Otherwise, we consider the acquisition a diversification. Mixed horizontal/vertical integrations are assigned according to the start-up's primary NACE Rev. 2 division and, in case of residual uncertainty, we default to consider them vertical integrations. Moreover, we compare the headquarters' location of the start-up and the acquiror(s) to differentiate between national, international and intercontinental (i.e. extra-EU) mergers and acquisitions.

The corporate group information collected in the previous steps also feeds into a number of indicators that we employ in our propensity score matching model. Notably, the number of shareholders results from the above calculations. Moreover, we include an indicator of the "ownership type" in a given corporate group. This is defined as follows: a) Corporate majority shareholder, i.e. a single corporation holds a controlling share in the start-up; b) Corporate plurality shareholders, i.e. a group of corporations hold a controlling participation in the start-up; c) Non-corporate majority/plurality shareholder/s, i.e. one or more natural persons hold a controlling share in the start-up.

One additional corporate group index — the independence indicator — is directly provided by Bureau Van Dijk. The indicator characterises the degree of independence of a company with regard to its shareholders. The independence indicator only considers shareholders that are capable of exerting a controlling power over a company.[33] We use a simplified version of the indicator that takes values A, B, C, D or "unknown". Independent companies have score A and no known recorded shareholder having more than 25% of direct/indirect ownership. Companies with independence score B have one or more shareholders with an ownership percentage above 25%, but no known shareholder with more than 50% of direct/indirect ownership. Companies scored C have a shareholder with more than 50% of indirect ownership, while companies scored D have a shareholder with more than 50% of direct ownership. Companies that do not fall into the previous categories are classified as "unknown", i.e. with an unknown degree of independence.

[33] For instance, shareholders of public companies are not considered able to exert a controlling power.

B Competing risks methods

This technical appendix provides an overview of competing risk methods. Let k represent a number of potential exit events that occur at time $E_1, E_2, \ldots, E_k$ respectively. For a given start-up, we cannot observe $(E_1, E_2, \ldots, E_k)$. We observe instead the exit time $T = \min(E_1, E_2, \ldots, E_k)$, and the exit status $\delta(T) = k$ if $\min(E_1, E_2, \ldots, E_k) = E_k$. We are also in the presence of right censoring, meaning that we might not be able to observe T if it still has to occur, i.e. if T is larger than some censoring time θ. In that case, we observe no exit event and $\delta(\theta) = 0$.[34] Note that the exit status $\delta(t)$ is a function of time and $\delta(0) = 0$, i.e. at $t = 0$ the start-up has not yet experienced any exit.

The key parameters in competing risks analysis depend on the type of desired inference. Of relevance are the cause-specific hazard rates $h_k(t)$. The function $h_k(t)$ represents the instantaneous risk of experiencing exit outcome k at time t, given that the start-up still has not faced any exit event by then:

$$h_k(t) = \lim_{dt \longrightarrow 0} \frac{\Pr(\delta(t + dt) = k \,|\, \delta(t) = 0)}{dt} \tag{1}$$

In addition to the cause-specific hazard rates, we may be also interested in the so-called cumulative incidence function (CIF) for exit event k, written as $C_k(t)$. The function $C_k(t)$ represents the probability that a start-up will experience exit outcome k by time t, accounting for all other exit types.[35]

In the presence of competing risks, the function $C_k(t)$ does not only depend on the cause-specific hazard $h_k(t)$, but on the entire set of hazards $h_j(t)$, with $j = 1, 2, \ldots, K$. For instance, to calculate the function $C_k(t)$ when k is IPO, we need to know the probability that the start-up does not experience any other exit type until time t. For k competing risks, it can be shown that the probability that no exit event has ever occurred by time t, i.e. the duration (or survival) function $S(t)$, equals to:

$$S(t) = 1 - C_1(t) - C_2(t) - \ldots - C_k(t) \tag{2}$$

Intuitively, since (by definition) at $t = 0$ the start-up has certainly not faced an exit event (i.e. $S(0) = 1$), we can compute the probability that said start-up will still not have experienced any exit outcome at time t by subtracting from the initial state the CIF of every exit outcome at time t. Note, however, that $C_k(t)$ is not a proper distribution function, since $\lim_{t \longrightarrow \infty} C_k(t) < 1$. For this reason, $C_k(t)$ is called a sub-distribution function (Klein *et al.*, 2014). The CIF can be expressed in terms of (1) and (2):

$$C_k(t) = \int_0^t h_k(u)\, S(u)\, du \tag{3}$$

There are two well-established approaches to estimate a competing risks model. The first is to fit the cause-specific hazard function $h_k(t)$ via a Cox regression model (Cox, 1972). However, there are significant drawbacks to this approach. First, this strategy does not allow researchers to draw a direct relationship between the cumulative cause-specific incidence and a given covariate of interest. This is

34 We actually observe $T^* = \min(T, \theta)$, $\delta^* = \begin{cases} k & \text{if } T < \theta \\ 0 & \text{if } T > \theta \end{cases}$. Our lighter notation is without loss of generality.

35 Formally, $C_k(u)$ for a given time u is defined as follows: $C_k(u) = \Pr(t \leq u, \delta(t) = k)$.

because, as shown in (3), the CIF is a function of all cause-specific hazards (Andersen and Keiding, 2012). Secondly, this approach assumes independent censoring. That is, the different competing events (and the lack thereof) must all be independent from each other. For instance, when studying IPO exits, any censored company at time t would need to have the same probability of exit through an IPO, regardless of whether the reason for censoring is an acquisition or bankruptcy. Unfortunately, this assumption cannot be tested in the data, since we cannot observe whether a firm exited via an acquisition would have otherwise experienced e.g., an IPO in the absence of the former.

Against this backdrop, another widely-used approach is the Fine and Gray (1999) proportional hazards model for the sub-distribution $C_k(t)$, designed to overcome the limitations of the Cox regression in the presence of competing risks. The Fine and Gray (1999) model directly links $C_k(t)$ to a vector of covariates X, through the cause-specific sub-distributional hazard (sub-hazard) function $\lambda_k(t|X)$:

$$\lambda_k(t|X) = \frac{dC_k(t|X)/dt}{1 - C_k(t|X)} = -d\ln\left[1 - C_k(t|X)\right]/dt \tag{4}$$

The function $\lambda_k(t|X)$ can be interpreted as the instantaneous probability that a start-up experiences exit k at time t, given that it either faced no exit yet, or experienced any other exit route but k. Fine and Gray (1999) propose fitting a Cox model to the sub-distribution hazard $\lambda_k(t|X)$. They assume that $\lambda_k(t) = \lambda_{k0}(t)\exp\{\beta' X\}$, where $\lambda_{k0}(t)$ is the baseline sub-hazard function. Rearranging the terms in (4) to express $C_k(t)$ as a function of $\lambda_k(t)$, we obtain the cause-specific regression model:

$$C_k(t|X) = 1 - \exp\left\{\int_0^t \lambda_{k0}(t)\exp\left\{\beta' X\right\} du\right\} \tag{5}$$

The Fine and Gray (1999) model displays many of the useful features of the Cox model while also allowing for unbiased inference in the presence of competing risks. However, the model also comes with its own set of limitations. In particular, the quantitative interpretation of its regression coefficients is not trivial. This is because they are related to the sub-hazard function $\lambda_k(t|X)$, which as mentioned above includes in the "at risk" category all start-ups that still have not experienced an exit event as well as those that experienced an exit outcome other than k. This is somewhat counter-intuitive, since firms which have exited through, for example, an acquisition before time t, are not really "at risk" of exiting through an IPO at time t.

Recently, Geskus (2011) proved that the Fine and Gray (1999) model can also be estimated using a weighted version of standard survival estimators for e.g., the Cox proportional hazard model. In this framework, we are able to estimate confidence bounds for the survival/incidence curve and carry out auxiliary statistical tests (Lambert, 2017), such as the one discussed in Gray (1988). In addition, Lambert (2017) discusses a series of estimators based on the Royston and Parmar (2002) flexible parametric survival model. These allow us to fit survival data and generate smooth versions of the traditional non-parametric Kaplan–Meier survival curves, which still account for competing risks.

C Alternative matching strategies

In this section, we test whether employing less stringent matching techniques changes our estimation results. Instead of the nearest neighbour matching with calliper implemented in the main analysis, here we construct two alternative approaches.

The first one is nearest neighbour (NN) matching without calliper, i.e. we still match each treated firm to the control with the closest propensity score, however we do not put any constraints on how far away this score may be. The second approach we test is matching up to three closest neighbours (Rank 3) to each treated firm whose propensity score is within the set calliper. Naturally, the two alternative approaches result in more matched pairs than our original set-up.

Table C1 and Table C2 show the results from the two alternative matching strategies for our five main outcomes of interest as well as their baseline estimates from section 6, also reported here for comparison. The two alternative matching designs yield 696 and 982 matched firms respectively versus 548 companies in our baseline.

The results on the M&A exit type remain positive and significant irrespective of the implemented matching. We see, however, that in terms of magnitude our baseline result lies between the estimates of the two additional matching strategies. Moreover, the result produced with the nearest neighbour matching option is significant at the 1% level as opposed to the 0.1% level.

The estimates on IPO show increasing levels of both significance and magnitude as the analysed samples' sizes grow. If we match companies without calliper, we obtain significant results at the 5% level while the sample containing up to three matched controls yields results significant at the 1% level. The estimates obtained by including more observations in our analysis implies that venture capital likely plays a significant role in companies' placement on public markets, however we would need more data to confirm this with higher certainty.

The treatment dummy coefficients on Other Buy-outs remain insignificant. Therefore, we find no evidence even in augmented samples that VC supports this type of exit. Similarly, irrespective of the matching approach employed, we see no significant results of venture capital on firms' survivability. Conversely, irrespective of the matching design, VC-invested companies innovate significantly more than their counterfactuals. We note that all estimates are significant at the 0.1% level and very close to each other in terms of magnitude.

Table C1: Alternative matching strategies (pt.1): estimated odds ratios for the Cox proportional hazard model

	M&A			IPO			Other Buy-out		
	Baseline	NN	Rank 3	Baseline	NN	Rank 3	Baseline	NN	Rank 3
VC-invested	2.934***	2.079**	3.602***	3.327†	4.504*	5.719**	1.001	1.300	1.834
	(0.796)	(0.510)	(0.839)	(2.385)	(3.190)	(3.632)	(0.655)	(0.880)	(1.200)
Firm age at inv. year	1.058	1.071	1.081	0.995	0.961	1.028	0.921	0.982	0.889
	(0.070)	(0.062)	(0.059)	(0.153)	(0.156)	(0.131)	(0.155)	(0.158)	(0.146)
Predicted degree of innovativ.	1.061	1.081	0.981	3.184	2.142	3.614	0.463	0.433	0.500
	(0.344)	(0.282)	(0.273)	(2.918)	(1.592)	(3.285)	(0.448)	(0.364)	(0.439)
Patent at inv. year	0.583	0.553*	0.673	4.062*	1.863	3.340†	1.950	0.906	2.698
	(0.222)	(0.151)	(0.219)	(2.789)	(1.095)	(2.250)	(2.461)	(1.158)	(2.895)
Propensity score	4.930*	4.438***	7.772**	1.412	3.434	1.922	0.036	1.155	0.129
	(3.448)	(1.985)	(4.894)	(1.955)	(3.631)	(2.663)	(0.075)	(2.517)	(0.261)
Corp. group covariates‡	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-411.97	-595.04	-539.20	-64.01	-96.38	-74.03	-48.39	-62.24	-65.42
N° of observations	548	696	982	548	696	982	548	696	982
N° of exit events	75	103	91	12	17	13	9	11	11
Tot. time at risk (quarters)	14,351	18,056	26,027	14,351	18,056	26,027	14,351	18,056	26,027

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

Table C2: Alternative matching strategies (pt.2): estimated odds ratios for the Cox proportional hazard model

	Bankruptcy			Patenting		
	Baseline	NN	Rank 3	Baseline	NN	Rank 3
VC-invested	1.266	1.170	1.156	2.172***	2.062***	2.154***
	(0.219)	(0.174)	(0.159)	(0.349)	(0.313)	(0.305)
Firm age at inv. year	0.994	0.982	1.021	0.927	0.902†	0.917*
	(0.048)	(0.046)	(0.037)	(0.046)	(0.047)	(0.033)
Predicted degree of innovativ.	0.408***	0.431***	0.324***	1.914*	1.932**	1.874**
	(0.086)	(0.080)	(0.056)	(0.506)	(0.431)	(0.397)
Patent at inv. year	0.989	0.991	1.149	7.275***	7.089***	9.491***
	(0.217)	(0.194)	(0.224)	(1.699)	(1.337)	(1.918)
Propensity score	0.579	0.417*	0.488	2.105†	1.906†	2.319*
	(0.301)	(0.156)	(0.230)	(0.924)	(0.660)	(0.893)
Corp. group covariates‡	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-790.81	-1077.80	-1576.14	-727.82	-967.80	-1149.18
N° of observations	548	696	982	548	696	982
N° of exit events	137	180	249	133	169	194
Tot. time at risk (quarters)	15,835	20,038	27,744	11,378	14,471	21,117

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

D Alternative model specifications

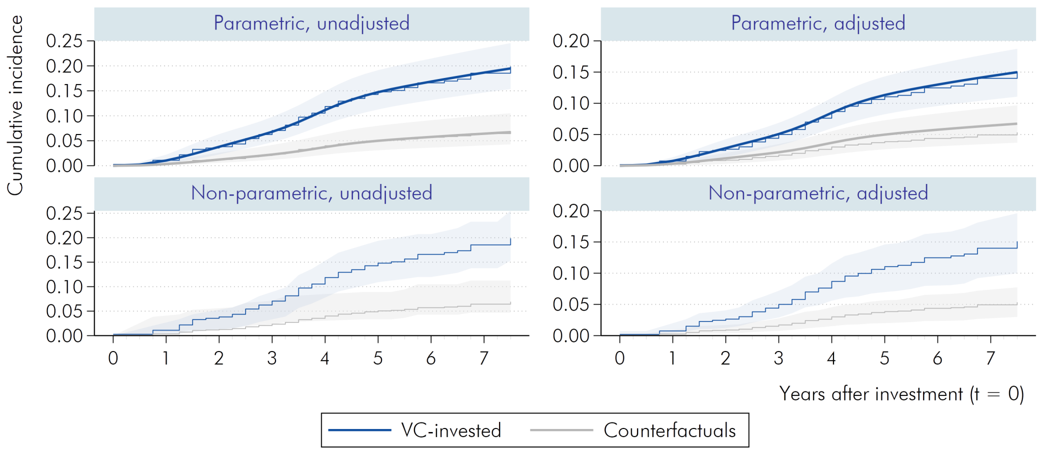
We provide here complementary estimates of the cause specific cumulative incidence function (CIF), first introduced in section 6. These stem from alternative model specifications and/or alternative estimators of the CIF. The baseline estimates of the CIF presented in section 6 are based on the Royston and Parmar (2002) model, which uses natural cubic splines to interpolate the cause specific CIF. Our baseline estimates do not control for potential covariate imbalance, to avoid over-fitting and other issues related to small sample sizes. For these reasons, our baseline estimates result from a parametric, unadjusted regression.

A more conventional approach to estimate the cause specific CIF entails the non-parametric estimator of Prentice *et al*. (1978). Geskus (2011) shows that such estimates can be reproduced by a weighted version of the Kaplan–Meier survival curve estimator. This alternative approach allows, in addition, to compute confidence bounds for the CIF.[36] Using bootstrapping, the software in Ruhe (2019) further allows the estimation of confidence bounds in the presence of covariate adjustment. It is important to mention that the non-parametric confidence interval estimates of the CIF are unable to account for the clustered nature of our matched sample (Austin and Fine, 2019).

Overall, we make use of four different approaches to estimate the cause specific CIF: a) via a parametric model and without further covariate adjustment (the baseline approach); b) via a parametric model with covariate adjustment; c) non-parametrically, without covariate adjustment; d) non-parametrically, with covariate adjustment. Accordingly, Figures D1-D5 provide, for each exit outcome in this paper, the difference between the treatment and control group's CIF according to each of the four estimation strategies.

Figures D1-D5 show that our baseline estimates are generally consistent across the different model specifications and/or estimation approaches. Figure D1 shows that covariate adjustment narrows down the distance between the treatment and control CIF for M&As, in line with the estimates of Table 6. The opposite happens in the case of Figure D5. We observe a slight discrepancy between the parametric and non-parametric CIF estimates in some charts. Interestingly, this seems to be driven by instances of over-fitting, which motivates the use of unadjusted estimates as our baseline approach.

Figure D1: M&A: changes in the CIF due to treatment



[36] Coviello and Boggess (2004) already address this in the case of univariate (unadjusted) changes in the CIF.

Figure D2: IPO: changes in the CIF due to treatment

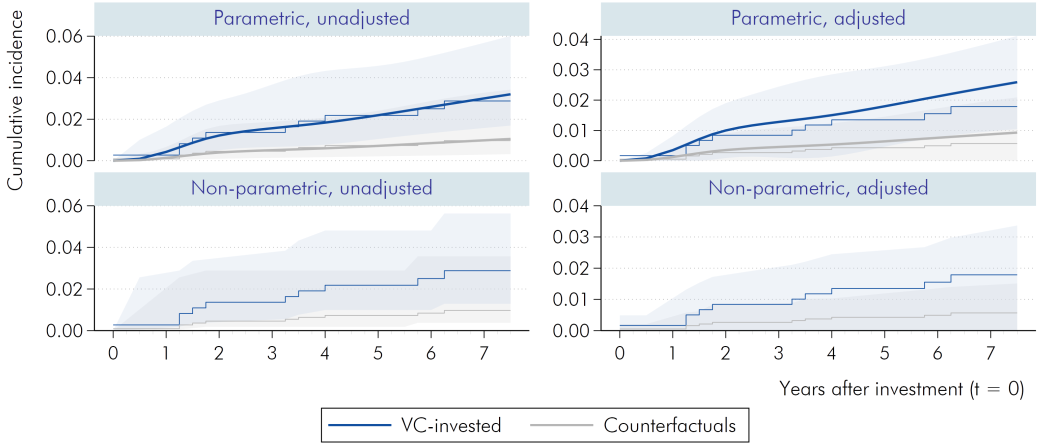


Figure D3: Other buy-outs: changes in the CIF due to treatment

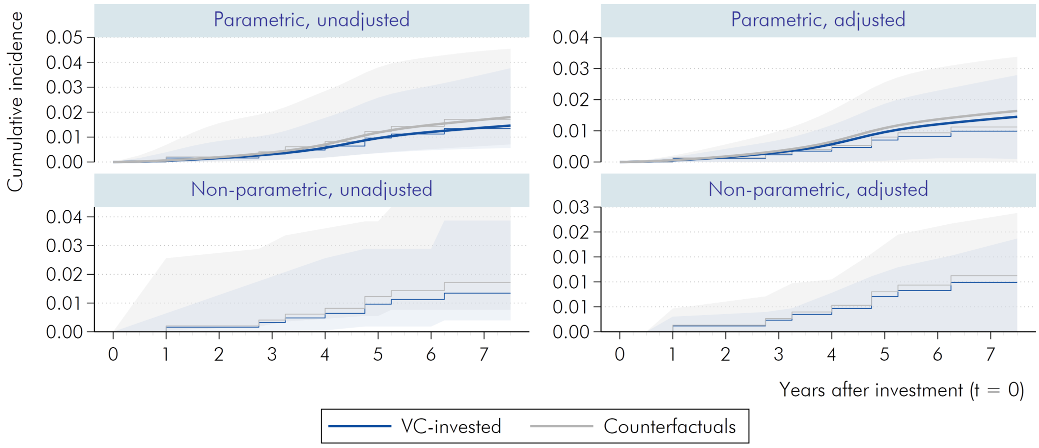


Figure D4: Bankruptcy: changes in the CIF due to treatment

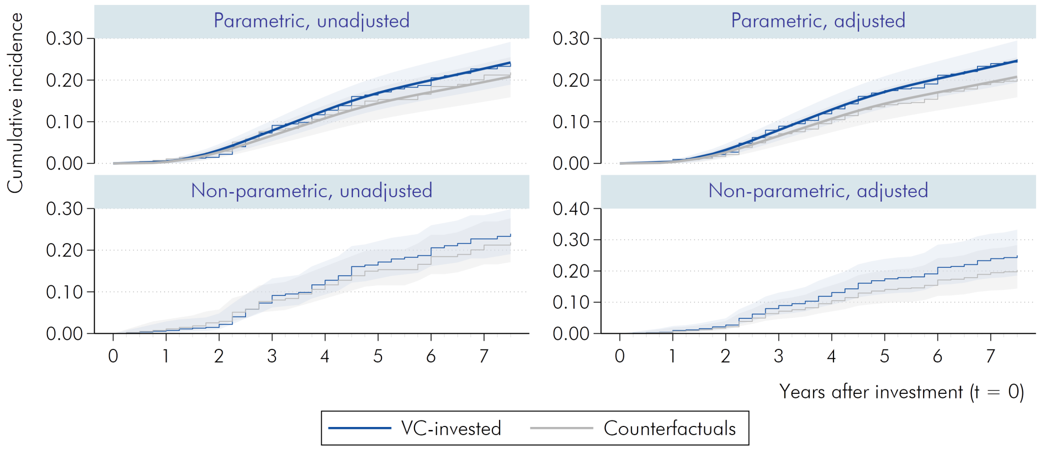
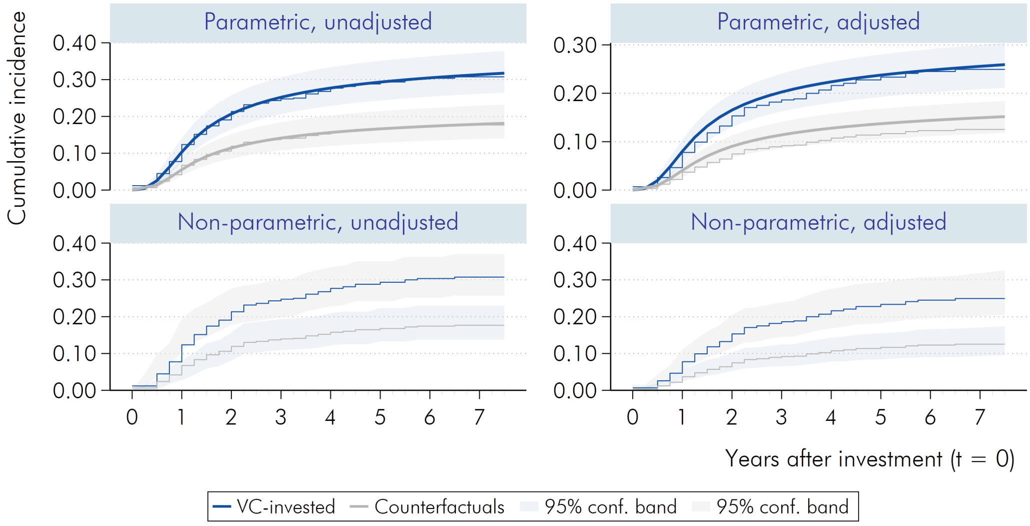


Figure D5: Patenting: changes in the CIF due to treatment



E Robustness to model misspecification

In this appendix, we perform three robustness checks to verify the validity of our main results. First, we check how sensitive our estimates are to misspecifications in the treatment assignment mechanism. We then test the continuous time assumption of our competing risks model by estimating a discrete time model for our exit outcomes and firms' survival. Finally, we trade the competing risks model for a simple OLS regression to estimate the effect of VC on firms' innovation activity.

Rosenbaum sensitivity analysis

One way to challenge our econometric approach and subsequent results is by questioning whether we have selected appropriate control companies for the VC-invested start-ups. The validity of our estimates hinges on the substitutability between the treated firms' results in a world without VC (unobservable) and the counterfactuals' (observable) results. If our treated firms are inherently different from their selected controls,[37] the difference between the two groups would not be attributable to the treatment, but rather to unaccounted features.

Rosenbaum sensitivity analysis (Rosenbaum, 2005) turns this identification problem on its head and asks instead, how much different can the two groups be while still allowing the detection of significant treatment effects. In this way, even if there is unobserved variable bias affecting our results, we show how large it needs to be to invalidate the significance of venture capital in the outcome regressions.

Table E3 shows varying levels of hidden bias, Γ, and the associated measure of statistical significance, the P-value, for respectively M&A, IPO and Innovation. We employ this analysis in the case of those outcomes for which venture capital has a significant effect. The sensitivity analysis results reveal overall robustness to hidden biases.

Table E3: Rosenbaum sensitivity analysis estimates

Γ	P-value		
	M&A	IPO	Patenting
1.0	0.000	0.072	0.000
1.1	0.000	0.097	0.002
1.2	0.000	0.125	0.007
1.3	0.000	0.154	0.019
1.4	0.001	0.184	0.043
1.5	0.002	0.215	0.084
1.6	0.004	0.247	0.144
1.7	0.008	0.278	0.222
1.8	0.013	0.309	0.314
1.9	0.022	0.340	0.413
2.0	0.034	0.370	0.512
2.1	0.050	0.399	0.475
2.2	0.070	0.427	0.386
2.3	0.094	0.455	0.307

Note: The P-value on the Patenting estimates rises first and then falls. This is the case since Γ becomes so large that the estimated average treatment effect on the treated switches sign and becomes more significant again.

[37] For example, due to characteristics not captured by our matching methodology.

The effects of venture capital on M&A would still be statistically significant even if our matching model rendered treated companies more than twice as likely to receive VC investment than their controls. In the case of IPO, as noted in section 6.1 we are able to detect a baseline difference between VC- and non-VC-invested firms only at the 10% significance level. Therefore, the sensitivity analysis is not very informative in this instance, nevertheless we report the results for completeness. Finally, the effects of VC on Innovation are also relatively robust, they would still remain significant at the 5% (10%) level if VC-invested firms were 40% (50%) more likely to be treated.

Multinomial logit competing risks model

Survival models could be classified into two categories according to how they address the time dimension in the data, namely discrete time models and continuous time models (Jenkins, 2004). Survival data could be discrete if they have been grouped together into intervals or if the underlying data generating process naturally takes place in cycles. On the other hand, survival data are considered continuous if the event of interest occurs at a specific measured point on the time continuum.

Naturally, company exit data are generated continuously and indeed both models employed in our analysis (Cox, 1972; Fine and Gray, 1999) assume that survival times are measured on a continuous scale. However, our exit information is not continuous since it has been discretised to the first date of the quarter in which the event took place. In this section, we revert to a discrete-time setting, following the approach outlined in Jenkins (2004) in order to compare our results from the continuous case. We estimate a multinomial logit model, assuming independent risks and proportional hazards.

Table E4 shows the results in the alternative discrete-time framework for the four possible exit outcomes. We note that the four coefficients are very close in both magnitude and significance to our baseline estimates, which can be referred to in Table C1 and Table C2 in section C. The only exception is the estimate on bankruptcy, which is now significant at the 10% level. Overall, the results from a discrete time setting validate the estimates of our main continuous time models.

Table E4: Multinomial logit competing risks analysis: estimated odds ratios

	M&A (1)	IPO (2)	Other Buy-out (3)	Bankruptcy (4)
VC-invested	3.099***	3.234†	1.038	1.369†
	(4.15)	(1.74)	(0.05)	(1.71)
Firm age at inv. year	1.080	0.976	0.941	0.998
	(1.19)	(-0.15)	(-0.31)	(-0.05)
Predicted degree of innovativ.	1.218	2.963	0.515	0.442***
	(0.65)	(1.17)	(-0.77)	(-3.70)
Patent at inv. year	0.505†	3.943*	2.019	1.140
	(-1.86)	(1.99)	(0.76)	(0.51)
Probability of treatment	4.602*	1.412	0.0337	0.400
	(2.49)	(0.25)	(-1.31)	(-1.59)
Corporate group	Yes	Yes	Yes	Yes
Nr of Observations	14,895	14,895	14,895	14,895
Log-Likelihood	-1282.60	-1282.60	-1282.60	-1282.60
LR Chi-Sq.	157.15	157.15	157.15	157.15
Chi-Square (p-value)	0.000	0.000	0.000	0.000
Pseudo-R-squared	0.06	0.06	0.06	0.06
Mc-Fadden R-squared	0.06	0.06	0.06	0.06
Adj. Mc-Fadden R-squared	0.03	0.03	0.03	0.03
AIC	2637	2637	2637	2637

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

OLS method applied to patenting activity

Since firms' patenting activity does not naturally fit into survival data context, here we opt for an ordinary least squares (OLS) regression to corroborate the effect of venture capital on firms' innovation efforts. More specifically, we regress the log of the number of annual patent applications on the treatment.

Table E5 shows the average treatment effects on the treated (ATTs) for the first six years after the investment. We note that VC-invested firms patent significantly more than their non-VC-invested controls in every period. The exact effect varies by period. For instance, VC-invested firms made 10% (16%) more patent applications in the second (sixth) year after they received their investment. Therefore, the alternative modelling approach confirms our main innovation results as well.

Table E5: Patenting activity: estimated ATTs, by post-treatment period

	ln(Number of annual patent applications)
ATT (Period 1)	0.1161***
	(0.033)
ATT (Period 2)	0.1038**
	(0.039)
ATT (Period 3)	0.1324***
	(0.039)
ATT (Period 4)	0.1383**
	(0.042)
ATT (Period 5)	0.0948*
	(0.042)
ATT (Period 6)	0.1613**
	(0.054)
Nr of Observations	4,393

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

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