Enabling or Accelerating? The Timing of Innovation and The Different Roles of Venture Capitalists

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Venture capitalists (VCs) shape innovative activities, moving beyond the role of providing financial resources. This paper investigates the role of VCs in firms' innovative performance regarding two mutually exclusive concepts in which they *enable* or *accelerate* the patenting activities, distinguishing previously patenting and non-patenting portfolio firms, respectively. To reveal underlying mechanisms, the analyses explore differences in the timing of patenting activities and the level of VC involvement using large-scale VC and firm-level data. We find a positive and persistent enabling effect, suggesting that VCs push for rapid commercialization of inventive ideas by previously non-patenting firms. While we find no accelerating effect on average, high investor involvement and reputable VCs can accelerate the innovative activity of patenting firms by fostering *new* ideas. Examining firm-level differences in prior patenting experience shows that some target firms rather seek financial support, while others additionally pursue active investor involvement that compensates for their need for expert knowledge. Overall, these findings disclose new and differentiated perspectives on the role of VCs in stimulating the inventive capabilities of their portfolio firms.

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1 Introduction

Nascent technology-based firms are particularly dynamic regarding their disruptive potential, knowledge spillovers, and innovative capabilities (e.g., Gornall and Strebulaev 2021; Schnitzer and Watzinger 2022). A sound financing environment is crucial for developing and exploiting these potentials (Hellmann and Puri 2002; Ewens *et al.* 2018). However, the financing activities of young, innovative firms are accompanied by severe information asymmetries and uncertainty. As specialized financial intermediaries, venture capitalists (VCs) can alleviate these agency problems through active involvement in the form of monitoring, governance, or providing expert advice (Bertoni *et al.* 2011; Bernstein *et al.* 2016; Lahr and Mina 2016). Thus, a common perception is that VC involvement contributes significantly to their portfolio firms' innovative capabilities.

In this paper, we examine the treatment effects of VC investors that shape firms' innovative performance. In particular, we consider two mutually exclusive concepts in which VCs may *enable* or *accelerate* the patenting activities of their portfolio firms. We define enabling as the initiation of patenting by previously non-patenting firms, whereas accelerating describes changes in patent activities of firms that had already been patenting before the initial VC investment. To investigate these treatment differences effectively, our analyses closely assess the timing of patent activities relative to the first investment and investigate distinct VC characteristics that determine their degree of involvement. These features allow us to provide a differentiated perspective on VC roles in the development of their target firms.

Studying a large-scale sample of nascent European firms, our baseline analyses show substantial differences in VCs' enabling and accelerating roles. VCs enable previously non-patenting firms' innovative activities by a combination of pursuing timely commercialization and a more persistent impact that allows target firms to patent successfully over time. Based on matched sample regressions, we estimate that the instantaneous probability of filing for a patent is 3.3 times higher for a VC-funded firm (i.e., without patents before the initial VC round) than for a comparable firm without funding. In contrast, for the average target firm with pre-VC patenting activities, we find robust evidence that there is no accelerating effect of VCs. The estimates are insignificant across different specifications and regardless of the examined treatment period or patenting dimension. Overall, the results are unlikely driven by selection effects and robust to using different model specifications, such as event study difference-in-difference regressions, hazard estimates, and Heckman-type estimates (see Fang 2005; Chemmanur *et al.* 2011).

Importantly, we investigate several VC characteristics to carve out key mechanisms regarding the degree of VC involvement. Most notably, we find a positive accelerating effect for pre-VC patenting target firms that are backed by highly involved VCs, such as CVCs and more experienced or reputable VCs. These effects arise two to three years after the initial investment, indicating that more sophisticated VCs foster *new* ideas. High VC involvement also moderately enhances the enabling effect of VCs. Moreover, investor involvement is most beneficial for target firms in cases in which firms benefit most from VCs' industry expertise. In the spirit of an inverted U-shape, the treatment effects are moderated if VC expert industry knowledge is either not required or likely insufficient, i.e., in industries with particularly low or high propensity to patent. Similarly, the effects of highly involved VCs are stronger for firms with little prior patenting experience. These findings provide novel evidence of the VCs' capabilities to enhance and accelerate patent activities even for targets with a proven record of patent activities before the investment. Additionally, they emphasize that distinguishing between different VC investors and the timing of the treatment effects is indeed crucial to evaluating the impact of VCs as specialized investors.

To guide the empirical analysis, we develop a conceptual framework that derives the enabling and accelerating roles of VC investors. The framework works out the relevance of the timing of innovative activities for evaluating the different roles of VCs. Since patent filings result from time-intensive research, short-term effects of VC investments are unlikely to reflect true enabling or accelerating but rather a change in the commercialization strategy of target firms. Furthermore, the framework also eludes to the key endogeneity concerns between investments and innovative processes and the timing of patenting activities. This is important since our analysis intends to examine differences in VC treatment effects, holding selection effects constant.

The integration of the conceptual framework into our empirical analysis is based on a sophisticated sampling procedure. It requires detailed information about the target firms, their inventive activities, and an appropriate comparison group. These features need to be observed for an extended part of firms' lifecycles from their earliest stages after incorporation to several years after the initial VC investment. We thus combine firm-level balance sheet data on firms across all industries (ORBIS) with information on individual rounds of VC investment (Thomson Reuters EIKON) and VC characteristics (Crunchbase) over 21 years starting in 1995. As a quantifiable and time-consistent dimension of firms' innovative performance, we follow related literature and consider patenting activities (Conti *et al.* 2013; Haeussler *et al.* 2014; Howell *et al.* 2020). To do so, we link sample firms to the worldwide statistical patent database (PATSTAT). In addition to this, the empirical analyses must account for differences across VC-funded versus non-VC-funded firms. Amongst others, our most fundamental approach to control for differences in observable firm characteristics is a rigorous matching exercise. Using Coarsened Exact Matching, we assign each VC-backed firm in our sample to a counterpart with comparable pre-investment observables, strictly delineating firms with and without patenting activities before the first VC round. This procedure leads to four mutually exclusive firm categories of two treated and control group firms, respectively: VC-backed firms that are either ex-ante patenting or non-patenting (treated), and the two corresponding non-VC-backed comparison groups (controls) that also distinguish ex-ante patenting and non-patenting firms. The final sample covers 9,614 individual European firms comprising 4,807 VC-funded and non-VC-funded pairs. Notably, the treated and control group firms are very similar regarding ex-ante matching criteria as well as other main features before and shortly after the initial investment, such as their investment patterns, growth, survival, performance, and overall demand for external financing.

Given the importance of VC investments for the trajectories of new firms, gaining a better understanding of their actual role in innovative processes is of chief concern for practitioners and governments alike. So far, empirical evidence on the role of VCs in fostering innovative activities, such as patenting, remains inconclusive. Some studies argue that VC investors' active involvement enhances their targets' long-run innovative performance (e.g., Samila and Sorenson 2011; Popov and Roosenboom 2012; Croce *et al.* 2013; Nanda *et al.* 2020). Others argue that VCs merely induce target firms to focus on sales as soon as the innovative process has been completed, i.e., without necessarily promoting their long-run innovative potential (e.g., Engel and Keilbach 2007; Peneder 2010; Arqué-Castells 2012; Lahr and Mina 2016).

Our analyses shed light on the role of VCs in the development of innovation-oriented firms along several dimensions. From a policy perspective, our findings provide new evidence on the controversial topic of evaluating the economic role of VC investors (see Lahr and Mina 2016; Lerner and Nanda 2020). Improving the understanding of the actual role of VCs in fostering technological inventions is vital for guiding policy attempts to spur entrepreneurial activities. Our results show that there are crucial differences regarding VC-related outcomes depending on investor-, firm-, and timing-specific dimensions, which highlights the need for a nuanced view when evaluating the potential effects of VCs. We thereby reveal important new facets of VC involvement in firm-level innovation activities and deliver possible explanations for the mixed evidence in previous empirical analyses. By developing a conceptual framework, we guide future research on the treatment effects of VC investments, particularly with respect to post-investment patenting dynamics. In addition, our findings also have practical implications, as they show under which conditions target firms benefit most from VCs' active involvement as a means to enhance their innovative capabilities. Overall, we provide a differential perspective on the role of VCs depending on the ventures' needs by delineating the enabling and accelerating effects for different types of investors and target firms.

2 Conceptual Framework and Data

2.1 Theoretical and empirical considerations on VC and patenting

Prior literature examines the effects of VCs for a variety of productivity-related, firm-level performance indicators (e.g., Chemmanur *et al.* 2011; Croce *et al.* 2013; Bernstein *et al.* 2016; Lerner and Nanda 2020). VC investors are a key component of the entrepreneurial financing landscape as they ensure the financing and mentoring of early-stage, high-risk, and innovative ventures (Hellmann and Puri 2002; Bertoni *et al.* 2011; Bernstein *et al.* 2016; Yu 2020). Thereby, VCs play a central function in innovative firms since they encourage and guide their portfolio firms spending on in-house research and development (Kortum and Lerner, 2001; Da Rin and Penas, 2007; Hirukawa and Ueda, 2011).

In this context, our analyses contribute to the literature on the implications of VCs' active role in monitoring and advising their portfolio firms. Such *post-investment* involvement is commonly referred to as the treatment effect of VC investors (Lerner and Nanda 2020). VCs aim to maximize their monetary returns by actively steering the commercialization strategy of their target firms' (technological) inventions. Post-investment involvement includes but is not limited to recruiting key personnel, developing business plans, and providing other industry-specific knowledge (Lahr and Mina 2016). Thereby, the characteristics of VC investors are essential in explaining their ability to generate value (Nahata 2008; Colombo *et al.* 2023). For example, VCs' experience and reputation are key determinants for explaining the long-term performance of their portfolio firms (Casamatta and Haritchabalet 2007; Sørensen 2007; Hochberg *et al.* 2007; Krishnan *et al.* 2011; Zhelyazkov and Gulati 2016). We follow this notion and investigate the enabling and accelerating effects of VCs, conditioning on these characteristics.

Importantly, VC-firm relations are multi-staged interactions in which post-investment activities naturally follow iterations of selection and matching, i.e., the *pre-investment* role of VCs. Within these processes, VC investors devote considerable time, effort, and financial resources to evaluating their investment opportunities (Gompers *et al.* 2020). To facilitate selection, they rely on quality signals, such as prior funding events, governmental grants, or proof of business activities, that indicate firms' ability to succeed in the transformation from conceptualization to commercialization (Hoenig and Henkel 2015; Islam *et al.* 2018). Patents can be one crucial signal as they are a reliable source of information approved by competent authorities (Haeussler *et al.* 2014; Howell *et al.* 2020). There are also firm-side factors that determine the likelihood of an investment deal being closed, such as entrepreneurs' willingness to accept certain contractual features (Drover *et al.* 2014).

These considerations on the VC investment process illustrate that patenting activities are both a prelude and a consequence of VC investments. Distinguishing these effects is non-trivial since the staged investment decision-making process entails obvious reverse causality issues. A priori, it is not clear whether VCs spur growth and innovation or whether they merely select high-growth, innovative firms. In the entrepreneurial literature, therefore, much attention is devoted to the important question of whether firm-level outcomes can be associated with the selection or the treatment effect of VCs (e.g., Bertoni *et al.* 2011; Croce *et al.* 2013; Lahr and

Mina 2016; Fisch and Momtaz 2020). So far, empirical evidence provides a rather ambiguous picture. Some studies document positive selection effects (Peneder 2010; Arqué-Castells 2012; Lahr and Mina 2016), while others find that the enhancing effects of VCs are not associated with VCs' selection abilities but rather with their post-investment involvement (Samila and Sorenson 2011; Popov and Roosenboom 2012; Croce *et al.* 2013; Nanda *et al.* 2020) or that the role of VCs is a combination of the two (Brander *et al.* 2002; Baum and Silverman 2004; Colombo and Grilli 2010; Bertoni *et al.* 2011).

Unlike these studies, our analyses approach the topic of VC involvement from a different angle: We focus on differences in the treatment effects, conditional on key features of target firms (patenting versus non-patenting) and investors (VC involvement in terms of experience and reputation). As shown above, deriving the effects of VCs on the patenting activities of their portfolio firms solely on the basis of ex-post performance would lead to considerable problems regarding endogeneity and reverse causality between investment and innovation activities. Accordingly, our analysis seeks to isolate the impact of VCs on post-investment patenting activity by correcting for the selection channel. To this end, we start by developing a conceptual framework in Section 2.2. The framework derives an empirical setting that allows us to, first, single out the enabling and accelerating roles of VC investors as treatment effects and, second, to mitigate endogeneity concerns arising from the preceding selection process. Section 2.3 then outlines how the empirical analyses incorporate these conceptual underpinnings from this framework.

2.2 Deriving the concepts of enabling and accelerating

Enabling versus accelerating: Patenting activities of VC-funded (δ_V) and non-VC-funded firms (δ_N) can be decomposed into activities before and after the VC-funded firms receive initial funding, that is, $\delta_V = V_{post} - V_{pre}$ and $\delta_N = N_{post} - N_{pre}$, respectively.[1] The average treatment effect of VCs on their target firms' patent activities, Δ_{avg}, comprises the changes in patenting of firms with (V) and without VC funding (N) that arise from VC involvement, ceteris paribus. For both sets of firms, the outcomes are also affected by other firm-, industry-, country-, and

[1] Intuitively, the pre- and post-VC investment periods for non-VC-backed firms (N) imply the occurrence of a hypothetical investment, i.e., the year in which a comparable VC-backed firm (V) receives its first funding.

time-specific characteristics (X'). As outlined above, selection effects may drive a significant wedge in the expression of these characteristics when comparing the average VC-backed and non-VC-backed firms. Hence, the average treatment effect of VCs on the patenting activity of VC-funded firms relative to firms without VC funding can be formally summarized as:

$$\Delta_{avg} = \delta_V - \delta_N = (V_{post} - V_{pre} + X'_V) - (N_{post} - N_{pre} + X'_N) \quad . \tag{1}$$

A key difference in the expression of X' is whether firms engage in patenting activities before initially receiving VC funding (1) or not (0). Indeed, post-VC patenting should systematically vary across pre-VC patenting and non-patenting firms (see, e.g., Bertoni *et al.* 2011). To incorporate this feature, we assess the average treatment effects for pre-VC patenting and non-patenting firms separately. More specifically, we define the *enabling* effect as the situation in which VC financing stimulates patenting activities for firms without patents prior to VC funding (V^0). As a complementary role, we collectively refer to the effect of VC involvement on patent outcomes of pre-VC patenting firms (V^1) as the *accelerating* effect.[2] The enabling and accelerating effects are mutually exclusive, implying that an individual VC target firm cannot be subject to both effects. For simplicity, we assume that key characteristics of VC-backed and non-VC-backed firms are quasi-identical in an ideal setting, i.e., $X' = X'_V = X'_N$. This assumption implies that it is thus vital to ensure that X' are as comparable as possible across the two groups of firms in the empirical analyses. Equation (1) can then be re-written as:

$$\Delta_{avg} = \delta_V - \delta_N = \left[(V^0_{post} - V^0_{pre}) + (V^1_{post} - V^1_{pre})\right] - \left[(N^0_{post} - N^0_{pre}) + (N^1_{post} - N^1_{pre})\right] , \tag{2}$$

where the average effect of receiving VC funding on firms' patent activities δ_V equals the average effect of firms without (V^0) and with (V^1) patenting activities prior to the initial funding round. Firms that do not receive VC funding (N) serve as a comparison group. These considerations yield four categories of firms: V^0, V^1, N^0, and N^1, as displayed in Panel A of Figure 1.

- Insert Figure 1 here -

[2]In line with literature that identifies a positive effect of VC funding on firm-level productivity outcomes (e.g., Lerner and Nanda 2020), the accelerating effect has an implicit positive connotation. Still, the accelerating effect can be positive, negative, or zero, whereas the individual effects (δ_V and δ_N) cannot be negative for firms without observable, pre-VC patenting activities by definition.

Rearranging Equation (2) further shows that the specific differences in pre-VC patenting activity require two separate analyses using two different estimation approaches. As such, for the enabling effect, the components V^0_{pre} and N^0_{pre} cancel out since these two firm types did not patent prior to VC funding (i.e., $V^0_{pre} = N^0_{pre} = 0$). Panel B of Figure 1 graphically illustrates the resulting conceptual ideas of enabling and accelerating. As it shows, the *enabling* (Δ_{ena}) and *accelerating* (Δ_{acc}) effects can be expressed as:

$$\Delta_{ena} = (V^0_{post} - N^0_{post}) - (V^0_{pre} - N^0_{pre}) = (V^0_{post} - N^0_{post}) \qquad \text{and} \tag{3}$$

$$\Delta_{acc} = (V^1_{post} - N^1_{post}) - (V^1_{pre} - N^1_{pre}) \qquad . \tag{4}$$

The timing of the effects: Equations (3) and (4) rather broadly capture the timing of patenting activities by considering pre- versus post-investment patenting. In fact, the timing of patent filings is essential for interpreting VCs' actual role in the innovation processes of their target firms: Patent outcomes are the product of medium-termed time-intensive research and development that realizes over time. This implies that there should be a substantial time gap between the initial idea creation, the development of a patentable idea, and its actual filing date. Hence, a patent application within the first years after the initial VC investment has most likely been initiated, irrespective of the VC involvement. Changes in patent activities right after the VC steps in then reflect – at least in part – a change in the exploitation strategy of existing ideas, i.e., the commercialization effect described in the literature (Arqué-Castells 2012; Lahr and Mina 2016; Lerner and Nanda 2020). In contrast, changes in patenting that result from the VCs' active involvement and know-how should instead become measurable in the medium term. This idea is in line with the view that investors with longer termed horizons strengthen governance and, thus, their targets' innovative capabilities in the long term (Harford *et al.* 2018).

Following this, the time gap between idea creation and a patent application has strong implications for evaluating the treatment effects of VCs. For patents filed within the first two years after the initial VC investment, we expect the original idea and possibly even the first development processes of a new technological invention already pre-existed. Only patents filed at a later stage are likely to be based on ideas generated after the initial VC investment. Hence, they should reflect the technological coaching capabilities of VCs more directly. For these reasons, our analyses devote much attention to the timing dimension in order to evaluate the roles of VCs in firms' patent activities consistently. Since the definition of distinct thresholds is prone to misspecification, our empirical analyses consider the overall evolution of post-investment patent activities over time. Without loss of generality, we assume that the development of an entirely new technology and the crafting of a patent, on average, takes at least two to three years, which would be equivalent to the average cycle times of new product lines (Cankurtaran *et al.* 2013).

2.3 Data and sample creation

Data sources: Our sample combines data from mainly three sources. Firm-level financial information comes from Bureau van Dijk's ORBIS database, which covers a broad range of European firms, including nascent ventures. We collected data for the EU15 countries for the years 1995 to 2015.[3] We augment this information with detailed data on patents and investors. The patent data comes from PATSTAT, which contains in-depth bibliographic information and characteristics covering the universe of patents filed in Europe. Orbis IP data contains a link between firm-level financials and PATSTAT, based on which we assign patent activities to respective firms. For the VC data, we use the Thomson Reuters EIKON database, which provides detailed information on individual funding rounds per firm. We enrich this data by adding specific investor and investment information from the Crunchbase database. We link the firm-level financial and VC data using string matches of names supplemented with information on the firms' locations and legal forms. To ensure a precise matching, we exclude firms with a matching probability below 95% and manually check all potential matches with a matching probability below 99.5%. The resulting data set comprises balance sheet, patenting, and VC investment information on all four types of firms as defined in the conceptual framework, i.e., the groups V^0, V^1, N^0, and N^1. Table IA1 (Appendix) defines all variables used in the analyses.

[3] The EU15 countries are all members of the European Union in the first sample year: Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, and Sweden. We determined 1995 as a starting date to warrant good data coverage. Choosing 2015 as the final year in the sample ensures that all firms can have an equally long post-treatment period. This cutoff is also beneficial as it helps to avoid truncation issues in the patenting data (see Lerner and Seru 2022).

Matching approach: The conceptual framework emphasizes the importance of keeping the covariates between VC-backed and comparison group firms fixed (i.e., X' in Equation 1) when estimating the enabling and accelerating effects of VCs. As the most fundamental step to address concerns regarding the endogenous funding decision of VCs, we follow related literature and use a matching approach that links VC targets to other firms with similar observable pre-investment characteristics (e.g., Yu 2020; Colombo *et al.* 2023). This approach is in line with the idea that VCs base their funding decision on traceable signals (Gompers *et al.* 2020) while facing a tradeoff in their selection process (Zacharakis and Meyer 2000): When trying to maximize their returns, VCs have an incentive to efficiently screen potential investment targets as well as to minimize costly selection efforts to the extend possible, e.g., by avoiding too complex signals (Van Balen *et al.* 2019; Colombo *et al.* 2023).

The matching procedure imposes several prerequisites that yield a set of potential matching candidates of non-VC-backed firms for previously patenting and non-patenting VC-funded firms. First, potential non-VC-funded matching partners have to share the same country of residence, industry affiliation (NACE main category), and founding year with at least one VC-funded firm. Second, in line with the conceptual framework, firms can only be paired when they have (N^1) or have not (N^0) filed any patent application before the matching year.

Out of these firms, we determine the closest neighbors using Coarsened Exact Matching (CEM). Specifically, we pair pre-VC-patenting (V^1, N^1) and non-patenting firms (V^0, N^0) and match them based on their size (log assets), year-to-year asset growth, a very granular industry level (4-digit NACE), and the number of patents filed. For VC-funded patenting firms, the matching variables are computed for the average of the three years before initial VC investment. For firms without VC funding, we compute the time-variant variables in a three-year rolling window. The CEM procedure groups firms into strata that may contain any number of VC-funded, non-VC-funded, patenting, or non-patenting firms. We remove strata with only one VC-funded or non-funded firm and keep the closest non-VC-funded neighbor of any VC-funded firm within the respective strata to avoid heavily unbalanced group sizes. Respective distances are calculated by the squared difference of the matching criteria. Consistent with the conceptual framework, the enabling and accelerating effects are mutually exclusive, such that firms are assigned to exactly one of the four categories (V^1, N^1, V^0, and N^0).

This procedure results in a sample of VC-funded firms. Each of these firms has one matching partner with an equivalent location, industry, age, and patenting activities, as well as very similar firm size and growth dynamics during the pre-VC period. For the comparison group, the pre-VC investment period refers to the years before their matched VC-funded counterpart receives the first VC funding round. The large sample size of non-VC-funded firms allows us to obtain very similar firm pairs of patenting and non-patenting firms, which aligns with the idea that covariates should be similar for these two subgroups (see Equation 1). Consistently, robustness tests show that the main effects are attenuated when considering VC-backed firms' average matching partner per strata. Table IA2 (Appendix) provides the t-statistics on the matched sample and shows no statistically significant differences among these groups for key observable characteristics before the initial VC round (Panel A).

Notably, the matching approach also addresses concerns about VC-funded and non-VC-funded firms being on (ex-ante unobservable) different trajectories.[4] This aspect is essential in light of the interdependence of VC investment cycles and firms' innovation patterns (Nanda and Rhodes-Kropf 2013). Panel B of Table IA2 shows that the survival rates in the initial years after the VC investment are comparable for treated and control group firms. This speaks against significant performance differences at inception. Moreover, Figures IA1 and IA2 (Appendix) show that firms are clustered in specific geographical regions and evolve along very similar trajectories. For example, there is no statistically significant difference among the treated and control groups regarding their size, investments, and dependence on external financing before and after the initial VC investment, diverging only on the medium- to long-term. These patterns speak against concerns that VC-funded firms are at different (unobservable) stages of their growth trajectories at inception. Moreover, they suggest that VC-backed and control group firms initially have a comparable funding demand.

The final sample covers 21 years (1995-2015) and includes all firm-year observations spanning three years before the initial VC investment up until ten years afterward. It contains 64,768 firm-

[4]In part, the matching approach reduces this concern by construction as it requires observations in the pre-VC period, and the age at the initial funding is a strict matching criterion. With a median age at funding of four years, most sample firms have overcome their most vulnerable lifecycle stage.

year observations, comprising 9,602 individual firms. By construction, half of the sample received VC funding at some point in time. At the time of the first VC investment, sample firms were fairly young and small by definition, with a median age of 4 years and size of 11 employees.[5]

2.4 Descriptive statistics

Table 1 displays the summary statistics on the main variables of the full sample. Overall, firms are very small, with relatively low levels of profitability and cash flows but a notable share of intangible assets (about 20%). All of these features are consistent with the objective of our study to examine VC-backed, innovation-oriented target firms and their matched counterparts. Similarly, most firms belong to industries known for a high propensity to patent or to attract VC funding, such as information and communication (26%), manufacturing (21%), and professional, scientific, and technical activities (20%). Consistently, pre-VC patenting firms are more concentrated on manufacturing (46%) and professional, scientific, and technical activities (32%). VC activity is concentrated in the largest economies in the sample, with around 60% of the firm pairs being located in France, Great Britain, and Germany.

- Insert Table 1 here -

Next, we assess the patenting activities of the sample firms in more detail. Overall, 15% of firms eventually file at least one patent. This number is higher for VC-funded firms (18%) than for non-VC-funded firms (12%). Around 6% of firms file for at least one patent before the initial VC investment, which is by definition the same for VC-funded and non-funded firms.

Figure 2 plots the evolution of patent filings relative to the year of the initial VC investment. The graphs emphasize the importance of considering pre-VC inventive activities when analyzing patenting as a treatment outcome. Panel A compares the average VC-funded firms (V) and their non-funded matched partners (N), irrespective of their pre-VC patent activities. While there are no statistically significant differences in the number and timing of patent filings between the two groups before the initial VC funding round, the average VC-funded firm files significantly more patents after the initial VC investment than the non-VC-funded comparison group during the

[5]Note that especially for young firms, information on the number of employees is often missing, which likely inflates the employee counts. The median number of employees for the full sample is 17 (see Table 1).

same time. However, this picture is quite different when differentiating between firms with and without patent filings prior to the initial VC round. Panel B displays the patenting activities of pre-VC non-patenting firms (V^0 and N^0) and shows a large and persistent wedge in the number of patents filed with significantly more patent filings by VC-funded firms. On average, 10% of VC-funded firms file for at least one patent after receiving the initial VC investment round in any subsequent observed period. In contrast, only 2% of non-VC-funded counterparts start patenting. Notably, Panel C compares the two groups of pre-VC patenting firms (V^1 and N^1). Here, we find no significant difference in the number of patent filings between the VC-funded and matched comparison groups. On average, however, VC-funded firms are still more likely to patent after the initial VC funding round compared to their matched counterparts (74% versus 64%). Figure IA3 (Appendix) demonstrates that these patterns are not driven by young firms entering the database and that the timing of patenting before the initial VC investment is very similar across the subgroups. Overall, the stark differences in the patterns of Panels B and C already indicate that it is essential to take pre-VC patent activities into account when analyzing the effect of VCs on their targets' innovation activities.

- Insert Figure 2 here -

3 Methodology and baseline results

3.1 The enabling role of VCs

Empirical Strategy: The enabling effect is defined as the difference in post-VC patenting activities of VC-funded firms (V^0) and firms without VC funding (N^0), conditional on not having any patents filed prior to the initial VC investment. To quantify this effect, we use survival analyses. This approach is beneficial as it is valid if the timing of an outcome is not normally distributed across time, and it accounts for potential right censoring issues in the data, both of which likely apply in our setting. Formally, we estimate the following Cox proportional hazard model:

$$h(t|z_{itcjs}) = h_0(t)exp(\beta VC_i + \beta_k Z' + \alpha_c + \alpha_j + \alpha_s) \,, \tag{5}$$

where i indexes firms, t indexes strata-specific years measured relative to the year VC-funded firms received the first funding round, c indexes countries, s indexes industries, and j indexes calendar years. The hazard rate $h(t|z_{itcjs})$ represents the instantaneous probability of a patent application for each firm and is determined by a set of covariates and h_0, the baseline hazard which does not need to be estimated in the model. VC_i is a dummy equal to one for firms that receive VC funding and zero for firms from the comparison group. Z' is a vector of control variables comprising the following observable, time-varying firm characteristics: total-debt-to-asset ratio ($DebtRatio$), size ($FirmSize$), profitability ($Profitability$), cash flow ($CashFlow$), and the share of tangible assets-to-total-assets ($Tangibiliy$) as defined in Table IA1 (Appendix). Further, we control for country-, time-, and industry-specific effects such as VC market developments or macroeconomic fluctuations by adding country (α_c), calendar year (α_j), and industry (α_s) fixed effects. The results are robust to using interactions of the fixed effects. Standard errors are clustered at the firm level.

The coefficient of interest is β. It captures the average differential probability of a patent filing for VC-funded firms relative to their matched non-VC-funded firms. A positive β indicates the presence of an enabling effect. To estimate Equation (5) using hazard estimations, we restructure our sample of pre-VC non-patenting firms to a firm-year panel that removes all years before the VC target receives initial funding (t=0) and those after the firm-specific year in which the respective firm files a patent application for the first time.

Baseline results: Table 2 displays the results of the Cox regressions using different variations of Equation (5). Column 1 displays estimates similar to the baseline model but without fixed effects. The coefficient of interest is positive and statistically significant at the one percent level. Adding country-industry and country-year fixed effects as defined in Equation (5) yields very similar results (Column 2). This baseline effect is economically significant; The coefficient (1.360) implies that the instantaneous probability of filing a patent is about 3.36 times higher for a VC-funded firm than for the comparison group.

- Insert Table 2 here -

Further tests mitigate concerns that VCs enable their target firms only file more but qualitatively inferior patents. To show this, we repeat the estimations but use a dummy as the main dependent variable that equals one if a firm files at least one patent with a minimum of one citation (Column 3) or one patent in the top quartile of the patent citation distribution (Column 4), and zero otherwise. For both definitions, the coefficients on the VC dummy remain highly significant. For patents in the top quartile, the coefficient is also much larger than the baseline estimate (2.139 versus 1.360). Moreover, firms with one-time patents are unlikely to bias the baseline results. This result is important since one-time patenters could occur randomly and, thus, unrelated to the VC investment. Specifically, the regression displayed in Column 5 repeats the baseline estimation but allows for multiple failures. The VC coefficient remains positive, highly significant, and even increases in size. Overall, the Cox model estimates show that VC-funded firms are associated with a significantly higher average probability of filing for patents after a VC investment. This average effect is persistent and even more pronounced when the measures of patent quality instead of quantity are taken into account.

For robustness, we examine the main enabling effects for several subgroups (see Table IA3, Appendix). The results apply to firms that survive only the initial years after first funding and those that survive longer (Columns 1-3), and to firms across age classes (Columns 4-6), with the effects being more pronounced for younger firms. Further, the main findings on the enabling effect apply to firms irrespective of the size of the first funding round (Columns 7-9) and irrespective of whether they receive follow-on VC investments (Columns 10-12). In the latter case, the results are significantly stronger for those with follow-on VC investments, which is consistent with a long-run enabling channel of VC investments.

3.2 The accelerating role of VCs

Empirical Strategy: For estimating the accelerating effect, we use a canonical difference-in-differences (DID) approach, including a full set of fixed effects, that exploits the panel structure of our data. In line with our conceptual framework, this approach uses two comparable groups, out of which one receives an investment (treatment) at period t=0, and the other one does not. We stack the data by defining the panel on the strata-specific years relative to the initial VC investment (t) and not based on calendar years (j). This method is advantageous because it avoids issues arising from staggered treatments in two-way fixed effects DID panel estimations (Baker *et al.* 2022). Further, we follow the most recent standards and do not bin the earliest and latest periods (i.e., those more than three years prior or eight years after the strata-specific VC investment year) but remove them from the estimations (see Sun and Abraham 2021). Formally, the following DID regression estimates the accelerating effect for the matched sample of pre-VC patenting firms:

$$Y_{itcj} = \alpha_i + \alpha_t + \alpha_{cj} + \beta\,(VC_i \times Post_t) + \gamma' Z_{it} + \varepsilon_{it}\ , \tag{6}$$

where all indexes are equivalent to Equation (5). The main dependent variable, Y_{itcj} is the logarithm of the number of patent applications filed; α_i, α_t, and α_{cj} are firm, relative year, and country-calendar year fixed effects, Z is a vector of control variables, identical to the vector used in the survival analysis, and ε is the error term. VC is a dummy equal to one for firms that receive VC funding. $Post$ represents a firm-specific dummy variable that equals one for all years after the initial VC investment is received by firm i. Hence, the interaction term $VC \times Post$ equals one if a firm receives VC funding for the first time in the firm-specific year t=0 and all subsequent periods and zero otherwise. The main coefficient of interest is represented by β and captures the average additional effect of receiving VC funding on firms' patent activities. Positive values of β indicate an accelerating effect. Again, standard errors are clustered at the firm level.

Baseline results: We estimate Equation (6) to quantify VCs' accelerating effects. The results in Table 3 show no differences in patent filings after the initial VC investment between VC-funded and non-VC-funded firms. The coefficient of the interaction term $VC \times Post$ is positive but statistically insignificant, irrespective of the use of fixed effects (see Columns 1 and 2). The insignificant coefficient for the VC variable shows that, on average, there is also no difference prior to the first VC round, which confirms our matching approach.

- Insert Table 3 here -

For consistency, we test this relationship in two alternative ways. First, β resembles the average effect over the entire post-VC period and, thus, may not capture any temporary accelerating effects. Estimates in Column 3 deploy an alternative *Post*-dummy, which equals one only in the years two to four after the initial investment (*Med-Post*). This way, we can detect temporary accelerating effects at times when we assume that a capability-driven accelerating effect should be observable (see Section 2.2). The small and insignificant estimate in Column 3 suggests that, on average, there is also no temporary accelerating effect. Second, another explanation for the insignificant estimates could be that VCs do not raise the number of patent filings but patent quality. To examine this, we repeat the previous specifications but use a citation-weighted measure of patent filings as the dependent variable. This adjustment does not yield different results (see Columns 4 and 5).[6] In sum, the baseline estimates on the accelerating effect do not support the idea that the average VC accelerates the patent activities of pre-VC patenting targets.

4 The timing of post-investment patent activities

4.1 The timing of the enabling effect

Empirical Strategy: As outlined in the conceptual framework, the timing of the effects is crucial to evaluate the roles of VC investors. To assess the timing of the enabling effect, we follow related literature and use a switching regression with endogenous switching (Fang 2005; Chemmanur *et al.* 2011; Yu 2020). This method is commonly applied to control for selection effects, requiring two estimation stages: First, a two-step Heckman-type approach and, second, a prediction of the firm outcome of interest (i.e., patent activities) across firms and time. Beginning with the Heckman-type estimations, we estimate the following latent VC-firm matching equation,

$$I_i^\star = Z_i'\gamma + \varepsilon_i \ , \tag{7}$$

where $I^\star$ is discretized such that I_i equals one if a firm receives VC funding and zero otherwise. The vector Z_i contains the same time-varying, firm-specific controls as in Equations (5) and (6):

[6] Supporting our model specifications, indeed, all estimates on the control variables have the expected signs. For example, the negative signs on profitability and age suggest that firms in the early stages of their lifecycle have a higher instantaneous probability of becoming first-time patentees. Consistent with the analyses on the enabling effect, we also show that the results are not biased by survivorship or firm age differences at initial funding, the size of the first deal, or follow-on VC investments (see Table IA4, Appendix).

$FirmSize$, $Profitability$, $CashFlow$, $DebtRatio$, $FirmAge$, and $Tangibiliy$. Equation (7) predicts the probability of receiving VC funding and yields consistent estimates of γ for previously non-patenting firms (V^0 and N^0), controlling for year, industry, and country fixed effects. These probit dynamic estimations allow us to compute the inverse Mills ratio.

The following two equations represent the second stage of the Heckman-type approach:

$$y_{1i} = x_i'\beta_1 + u_{1i} \; , \tag{8}$$

$$y_{2i} = x_i'\beta_2 + u_{2i} \; , \tag{9}$$

where Equations (8) and (9) estimate the effects of VC investments for VC-funded firms and their non-funded matched partners, respectively. We estimate both equations with an OLS and use the number of patent filings ($LogPatFilings$) or the citation-weighted number of filings ($CitsFilings$) as the dependent variable. The two equations include the inverse Mills ratio from the first-step probit estimation as an additional regressor. This approach mitigates concerns about unobservable characteristics influencing the selection of VC targets by implying a consistent estimation of Equations (8) and (9) using OLS (see Maddala 1986; Heckman 1979).

Estimating Equation (8) yields the predicted number of patent filings for VC-funded firms had they not received funding, whereas Equation (9) gives the hypothetical number of patent filings for non-VC-funded firms had they received VC funding. The comparison of these two values with the observed patent filing counts of respective subgroups marks the final stage of the switching regression with endogenous switching. It enables us to answer two hypothetical questions: What would the patenting of target firms be if they had not received VC funding? And what would the patenting of non-funded firms be if they had received VC funding? We compute the difference between the actual and the predicted number of filings for each year after initial funding, which maps the distinct timing of the baseline enabling effect.

Results: Table 4 displays the estimates of the switching regressions on the number of patent applications for each year after the initial round of funding (Panel A).[7] The estimates for the

[7]For completeness, Table IA5 in the Appendix displays the corresponding first-stage results (Panel A). The results remain qualitatively unchanged when including patent quality measures. Consistent with prior literature, patent citations relate positively to the probability of obtaining VC funding, while patent originality has ambiguous effects (Haeussler *et al.* 2014; Colombo *et al.* 2023). Panel B displays the estimates on the inverse Mills ratios, which are all positive and statistically significant.

VC-funded firms' predicted patent values (i.e., had they not received VC funding) are strictly lower than the realized values. The difference between those two values is negative and highly significant, both in the short and the long run. In the first four years following the initial VC investment, the number of patent filings is around three times higher than the predicted number had the firms not received funding. This difference increases for the subsequent years such that the actual number of filings is five to six times higher than the predicted one. In line with our previous results, the opposite is true for the non-funded comparison group: In the years after a hypothetical investment round, their hypothetical patent filings were higher by a factor of two to five had they received VC funding. Again, this difference is highly significant for the eight years following the hypothetical funding. Moreover, we show that the same pattern applies when using quality-adjusted patenting measures (see Panel B of Table 4). The difference for firms that receive VC funding is negative and significant in all periods following the initial investment round, indicating that the technological quality of the patents would have been significantly worse had the target firms not received VC funding. Again, the results are reversed for the non-funded matching partners.

- Insert Table 4 here -

Furthermore, we plot the baseline estimates obtained from the Cox regression over time to show that the specific methodological approach does not drive these results. Figure 3 displays the Nelson-Aalen cumulative hazard for the probability of patent filings during the eight years after the initial VC investment for pre-VC non-patenting firms. The difference between the two groups of firms is evident throughout the observed timespan and widens over time. This pattern is robust to focusing on high-quality patents (see Figures IA4, Appendix).

- Insert Figure 3 here -

In sum, the above-described results provide consistent and robust evidence of a persistent effect of VC involvement on target firms' patenting activities. Specifically, they show that there is a positive and sizable enabling effect of VCs that applies both in the short- and long-term and to patent quality. These effects indicate that VCs enable their target firms to patent already existing inventions right after the initial round of funding and spur innovative processes in the long run. Hence, enabling is not just about the realization of a short-term push toward rapid commercialization of the inventive output of target firms.

4.2 The timing of the accelerating effect

Methodology: We decompose the treatment effect (i.e., β from Equation 6) in an event study type specification for each year to analyze the changes in patenting after the initial investment. Formally, we use the following DID-estimation specification:

$$Y_{itcj} = \alpha'_i + \alpha'_t + \alpha'_{cj} + \sum_{S=-2}^{-3} \beta_1^S (VC_i \times Pre_t^S) + \sum_{S=0}^{8} \beta_2^S (VC_i \times Post_t^S) + \gamma Z'_{it} + \varepsilon'_{it} \quad . \tag{10}$$

where α'_i, α'_{cj}, and α'_t denote firm, country-year, and time fixed effects measured relative to the initial filing year. These factors are key in controlling for determinants of VC target performance, such as industry competition, the investment environment, or exit conditions (see Nahata 2008). We split the treatment indicator, $Post$, on a year-by-year basis: Pre^S and $Post^S$ are equal to one (and zero otherwise) for all observations S years before or after the initial VC investment, where $S \in [0, 8]$ or $S \in [-3, -2]$, respectively. The last year prior to the VC investment ($S = -1$) is the reference period. Hence, the estimates for S $\in [-3, -2]$ serve as a robustness test on parallel trends in the patenting activities of treatment and control group firms before to the VC investment. All remaining variables are specified as in Equation (6).

Results: Figure 4 plots the event study regression coefficients, $Post_t^S$ and Pre_t^S, from regressions that use $LogPatFilings$ as the dependent variable. The estimates show that the insignificant average effects estimated in the baseline regressions are stable across all observed years. As such, the coefficients are comparable in size, and none are statistically different from zero. Moreover, we find that VC-funded and comparison group firms move in parallel trends before the initial investment. These patterns also apply when using quality-based patent measures as dependent variables, an alternative matching procedure (see Figures IA5 and IA6, Appendix), and when re-estimating the switching regressions for the subset of pre-VC patenting firms (Table IA5, Appendix). The switching regression estimates imply that VC-funded firms would not have filed fewer patents if they had not received VC funding, which corroborates not only the findings in this section but also the general setting in Section 4.1. Overall, the estimates on the timing of the baseline accelerating effects underscore the baseline results.

- Insert Figure 4 here -

5 Mechanisms and heterogeneous treatment effects

5.1 Patent outcomes and VC involvement

In this section, we explore variation in investor characteristics to gain a more detailed understanding on the underlying mechanism behind the main results. Specifically, we investigate the differences in VC investors' active involvement and their relation to the strength of the enabling and accelerating effects. The main idea is that the treatment effects of VC should be greater if VC involvement is high, consistent with studies on long-term-oriented investors that stimulate innovation output over time (e.g., Harford *et al.* 2018). Since direct investor involvement is hard to quantify in observational data and to mitigate concerns regarding specific measures, our analyses use three distinct approaches to classify highly involved VC investors.

As a first measure of VC involvement, we follow previous studies which find that *corporate venture capitalists* (CVCs) are particularly involved investors. Indeed, CVCs have a higher tolerance for failure and specific technology know-how, both of which may stimulate the patent activities of their targets (e.g., Benson and Ziedonis 2010; Chemmanur *et al.* 2014). We identify CVCs using information from the Crunchbase database, which marks firms that act as both investors and regular organizations.

Despite the advantages of studying CVCs, their investment behavior and resources differ significantly from those provided by independent VCs (Guo *et al.* 2015; Colombo and Murtinu 2017). We thus compute two other measures of VC involvement relating to investors' experience and reputation that apply also to independent investors. The intuition behind choosing these two dimensions as relevant measures of investor involvement is straightforward. VCs fulfill several complex functions that require active involvement in addition to the mere provision of capital. Prior *experience* likely lowers these involvement costs, especially in specialized contexts such as patenting (Casamatta and Haritchabalet 2007; Bottazzi *et al.* 2008; Colombo *et al.* 2023). Consistently, studies have found positive effects of VC experience on startup performance, using age, cumulative investments, or VC networks as proxies for experience (Sørensen 2007; Hochberg *et al.* 2007). Moreover, investor *reputation* implies prior industry experience and, on top, superior managing, coaching, or advising capabilities of VCs that manifest in a superior performance record (Nahata 2008; Krishnan *et al.* 2011). A good reputation may be needed for the positive effects of experience to pay off as it facilitates repeated interactions with the target firms or other participants in financial markets (Zhelyazkov and Gulati 2016).

We follow existing literature to quantify VC experience and reputation. In line with, e.g., Sørensen (2007), we define VC experience (EXP) as the average number of deals among investors participating in the initial funding rounds observed in our sample. Further, we measure VC reputation as a determinant for VC investment outcomes in the spirit of Nahata (2008) by calculating the accumulated dollar market value of all targets that successfully exited via IPO or acquisition (REP). The measure is normalized using a time-varying aggregation of IPO and M&A market values in Europe since 1980. This approach builds on the idea that successful exits are the most salient indicator of a VC's past performance and that reputation requires continued success that creates visibility over time. We align with recent literature by considering both IPOs and acquisitions, suggesting that M&A and IPO exit strategies are equally important for VC reputation (Amor and Kooli 2020).[8]

We validate the relevance of these three investor characteristics using survival analyses. Figures IA8 and IA9 (Appendix) plot the unconditional probability (Kaplan-Meier failure estimates) of a successful exit by a VC-backed startup over time. First, Figure IA8 shows that there is no statistically significant difference in the probability of pre-VC patenting (V^1) and non-patenting (V^0) startups to succesfully exit either via an acquisition or an IPO. Second, during the first five post-investment years, there is also no difference in the probability of a successful

[8]Figure IA7 (Appendix) illustrates the prevalence of acquisitions compared to IPOs as the primary exit mode of new ventures, especially since the mid-2000s. Panel B displays the aggregate IPO and M&A market values that are used to compute the reputation measures. For robustness, we apply several variants of this measure.

exit comparing startups that are backed by either CVCs, experienced, or reputable independent VCs. This finding is important supporting evidence that VCs are not merely picking targets that promise quick returns but rather invest in innovation, i.e., longer-term returns. Third, the graphs also show that CVCs, experienced, and reputable investors are indeed able to yield higher exit rates in the long run. This observation is consistent with prior literature (Nahata 2008; Amor and Kooli 2020) and validates our measurement approach.

5.2 Treatment effects across different investor types

5.2.1 VC involvement and the enabling effect

We proceed by investigating whether the average enabling effect varies across firms funded by more or less involved VCs as measured by the three VC characteristics CVC, EXP, and REP. To do so, we modify the Cox regression specification from Equation (5):

$$h(t|x_{itcjs}) = h_0(t)exp(\beta_1 VC_i + \beta_2 \text{Invo}_m^{high} + \beta_3 VC_i \times \text{Invo}_m^{high} + \beta_k Z' + \alpha_c + \alpha_j + \alpha_s) \;, \quad (11)$$

where the involvement measures (Invo_m^{high} with $m \in [CVC, EXP, REP]$) are dummy variables that are equal to one for target firms which obtained their initial VC funding from CVCs, highly experienced VCs, or highly reputable VCs, and zero otherwise. In the latter two cases, we consider all VCs that rank above the median values of the overall experience or reputation distribution, respectively. The coefficient β_3 captures the additional effect of CVCs, particularly experienced, or reputable independent VCs on the instantaneous probability of patenting by a VC-funded firm. All remaining variables are specified as before.

Table 5 displays the results from estimating Equation (11). Across all specifications for $m \in [CVC, EXP, REP]$, the coefficient of interest for the interaction term $VC \times \text{Invo}_m^{high}$ is statistically insignificant (Columns 1-3). The interaction term is relatively large for startups with highly reputable investors but remains insignificant (Column 3). At the same time, the coefficients on the VC-dummies remain positive and highly significant across all specifications. Hence, distinguishing among target firms that are funded by VCs with relatively high or low involvement does not change the baseline estimates on the enabling effect. These results apply consistently when considering differences in patent quality, across alternative specifications of reputation, and controlling for survivorship or the number of investors (see Table IA7, Appendix). As before, they are not sensitive to the size of the first funding round but are more pronounced for startups with follow-on VC investments (see Table IA8, Appendix).

- Insert Table 5 here -

Columns 4-6 display estimations on the subsample of VC-backed firms only. Consistent with the first findings, there is no effect of CVCs or experienced independent VCs. In this specification, the coefficient on the high reputation dummy is positive and significant at the five percent level. Panel B of Table 5 shows that this pattern also holds when using the cumulative hazard rates on the likelihood of patenting over time. The differences in hazard rates between the VC-funded firms with high or low involvement VCs are insignificant in the early years after the initial VC investment, irrespective of the measurement approach. For CVCs, there are no differential effects throughout the first eight years after the initial investment altogether. However, for firms with either experienced or highly reputable investors, the likelihood of patenting is significantly larger than for those with other investors. Notably, this effect only emerges in the long term (i.e., after about five years), and, again, it is more pronounced for reputable VCs compared to experienced VCs. Consistent with the baseline results, these effects underscore the enabling role of VC investors. In sum, these results suggest moderate differences in the enabling effect among firms that are funded by more or less involved VCs. In particular, reputable investors can be associated with disproportional enabling effects.

5.2.2 VC involvement as a trigger for the accelerating effect

Next, we test whether high VC involvement has implications regarding the accelerating effect. To do so, we augment Equation (6) by adding a triple interaction term of the DID estimator ($VC \times Post$) with the indicator for highly involved VCs (Invo_m^{high}):

$$Y_{itcj} = \theta_i + \theta_t + \theta_{cj} + \beta' \left(VC_i \times Post_t \times Invo_m^{high}\right) + \vartheta Z''_{it} + \varepsilon_{it} \ , \tag{12}$$

where all variables are defind as before. For consistency, only the vector of control variables, Z'', now also includes the single components of the triple interaction term that are not absorbed by fixed effects ($VC \times Post$ and $Post \times Invo_m^{high}$).

Table 6 contains the results from estimating Equation (12) using the three definitions of highly involved VCs. As discussed in Section 4, the effects of VC funding on firms' patenting activities may only unfold with a certain time lag. As before, we thus use the two post-investment indicators, *Post* and *Med-post*. Across specifications, the coefficients for the triple interaction term, β', are positive and sizable. However, using the *Post*-dummy as the treatment variable, the coefficients are insignificant for CVCs and reputable VCs. For the average post-investment period, these estimates imply, at most, a moderately positive accelerating effect for firms funded by highly involved VCs. In contrast, across all specifications of VC involvement that deploy the *Med-post* indicator (Columns 2, 4, 6), the coefficients for the triple interaction are positive and significant at the one percent level. These estimates show that there is indeed a positive accelerating effect of VCs on their targets' patent activities. Importantly, this effect applies to firms conditional on having a CVC, an experienced VC, or a reputable VC and only with a time lag after the initial investment.[9]

- Insert Table 6 here -

We further explore the data to work out a set of important nuances of these findings. First, we use event study type regressions as introduced in Section 4.2 to underscore the accelerating role of VCs, conditional on being highly involved. It shows that there is no immediate effect on patent activities in the two years following the initial VC investment for firms with highly involved VC investors. Estimates turn significantly positive over the subsequent years before reverting to insignificant values by the fourth or fifth year after the initial investment, highlighting the importance to consider the timing of outcomes. Second, as another detail, the medium-termed accelerating effects for reputable investors are not driven by the size of initial funding amounts

[9] A series of robustness tests in the Appendix confirm these findings. First, the results are not sensitive to using different measures of patent quality or firms' patent stock (instead of filings) as the dependent variable (Table IA9). Second, the results are robust to controlling for survivorship (Panels A of Table IA10). Third, the results apply when using the number of successful exits instead of the market value of exits. However, they are much smaller when measuring VC reputation outside of Europe (Panel B of Table IA10). Further, estimations in Panel C show the role of syndications in the context of the accelerating effect is inconclusive. However, on average, there is a moderately positive accelerating effect on startups with syndicated first deals (Column 7).

but rather by sustained investments provided by highly involved VCs (see Table IA11, Appendix). Estimates for relatively small and large initial deal sizes are quite comparable in magnitude (Panel A), whereas the accelerating effects of highly involved VC are stronger for startups with follow-on VC investments than for those without (Panel B). This finding emphasizes the crucial role of providing VC investment in a multi-stage process.

Overall, these analyses show that VC involvement indeed has decisive implications for the patent activities of firms that had already been patenting before the initial VC investment, i.e., the accelerating effect. While the *average* pre-VC patenting firm does not disproportionally respond to VC investment relative to the matched control group, this changes with higher degrees of VC involvement. Specifically, pre-VC patenting firms with CVCs, experienced investors, and (in particular) highly reputable VCs disproportionally increase their patenting activities. Consistent with the idea that involvement mirrors interest regarding the medium- to long-term performance of targets, these effects only unfold two to four years after the initial investment. Since patenting activities during these years are most probably based on new ideas generated after the initial VC investment, these findings likely reflect VCs' coaching capabilities.

5.3 Firm-specific variation of VC involvement: Who benefits most?

While the previous analyses exploited differences across investor types, this section examines variation across target firms and, thereby, carve out further mechanisms and implications of the main results. The underlying idea of the analyses is that the effect of VC involvement should vary depending on target firms' demand for assistance: Some target firms may solely require assistance in monetary terms, whereas others may seek active investor involvement, compensating for the need for expert knowledge. Especially during the early lifecycle stages, different firms may have substantially different demands along these dimensions.

Pre-VC patenting and the relation between accelerating and enabling effects:
We start by analyzing the differential effects of active VC involvement depending on firms' level of pre-VC existing experience in patenting. To account for potentially decisive heterogeneity in firms' pre-VC patenting activities, we regard target firms' prior patenting intensity. In particular,

we assign firms to three similarly sized categories (small, medium, and large), depending on the size and the quality of their pre-VC patent stock. By construction, this setup only applies to pre-VC patenting firms (V^1 and N^1), i.e., for the accelerating effect. We re-estimate Equation 12 for each of the three subsamples separately. Results in Panel A of Table 7 show that firms with a small pre-VC patent stock primarily drive the additional accelerating effect associated with highly involved investors. The coefficients of the interaction terms are positive and highly significant for these target firms (Columns 1-3), while the coefficients are positive but insignificant for firms with medium-sized (Columns 4-6) or large (Columns 7-9) patent stocks at the time of the initial VC investment. This finding supports the results on the enabling effect as it shows that those firms that are most comparable to the pre-VC non-patenting firms drive the accelerating effect. Most importantly, it is consistent with the idea that investor involvement is most rewarding for those pre-VC patenting firms with relatively limited patenting experience.

- Insert Table 7 here -

Industry-specific propensity to patent and the treatment effects:

To delve deeper into this relationship, we analyze the differential effects of VC involvement in the context of firms' patenting experience using a more generalizable perspective. Inventive processes and their required resources differ considerably between the individual industries. In turn, the importance of VC involvement for stimulating patenting activities is likely different across industries. Firms that are active in industries with a particularly high propensity to patent, on average, should have a general understanding of the patenting process. Industry-level patenting intensity can thus be thought of as a broader measure of firms' patenting experience that applies to pre-VC patenting and non-patenting firms. Further, this appraoch is helpful as industry measures are likely exogenous to the business activities of the sampled firms.

We classify industries according to three groups based on a detailed assessment report of the EPO-EUIPO (2022). The report identifies 147 patenting-intensive industries in Europe, of which we consider the 50 most patenting-intensive sectors to be high-patenting-intensive. The other 97 patenting sectors are classified as medium-intensive sectors. All remaining industries not listed in the EPO-EUIPO report are labeled as low-patenting intensive sectors. Consistent with this classification, Figure IA10 shows that the main effects of the enabling and accelerating effects are moderately more pronounced in cases in which the VC investor has prior experience with targets operating in patenting-relevant sectors. Similarly, when using an augmented version of the baseline specifications that incorporates industry-level patenting differences, we find a positive association of the sectoral patenting intensity with firm-level patenting activities (see Table IA12, Appendix).

Most notably, we re-estimate the accelerating effect for the three industry groups. Panel B of Table 7 shows that the accelerating effect applies to CVCs, experienced, and reputable VCs, given that their target firm is *not* active in a sector with particularly high or particularly low patenting intensity. As such, the positive effects of VCs are mainly driven by firms in moderately patenting-intensive sectors. In high patenting-intensive fields, VCs' added experience with regard to technological inventions may not suffice to enhance patenting significantly. In contrast, in low patenting-intensive fields, VCs' expertise may not be required. This inverted U-shape relationship suggests that VC involvement is beneficial only if expert industry knowledge is important but not too far-developed.[10]

6 Conclusion

VCs are specialized financial intermediaries with several important roles in entrepreneurial processes, moving beyond the mere role of a financier. These roles comprise coaching and monitoring capabilities that are particularly relevant in the context of innovative processes, such as firms' patenting activities. In this context and in line with the resource-based view, we distinguish two specific mechanisms that elude to VC investors as a relevant factor integrating the financing, intangible, and human resource dimensions of nascent startups. As such, we are the first to assess the *enabling* and *accelerating* roles of VCs affecting their targets' patenting activities.

Our baseline results suggest that VCs act as enablers for firms that have not patented before they received initial VC funding, whereas, on average, there is no accelerating effect for firms that have patented before the VC stepped in. However, exploring heterogeneity in VC charac-

[10] These results are robust to adjusting the threshold between high and medium patenting intensity (undisplayed) and using citation-weighted patenting measures (Table IA13, Appendix). For the enabling effect, there are no significant differences across these industries (see Table IA14, Appendix).

teristics shows that *highly involved* VCs can trigger accelerating effects: Investments by CVCs, more experienced and, in particular, more reputable VCs yield a positive effect on the pre-VC patenting firms' patent activities. These findings provide evidence regarding the ability of highly specialized VCs to enhance patent activities even in cases in which targets already have a proven record prior to the engagement.

Furthermore, we find that the actual timing of outcomes is decisive when evaluating the role of VCs. Active VC involvement that yields new ideas should rather pay off over time because of the time-consuming processes of ideation and implementation. Indeed, the enabling effect appears right after the initial VC investment, but it also persists in the long term, which emphasizes that enabling is a combination of pushing rapid commercialization and actual mentoring of target firms. Regarding the accelerating effect, we find that highly involved VCs enhance the patenting activities of their targets with a delay of several years, suggesting that these VCs can foster *new* ideas for ex-ante patenting firms.

Finally, we investigate what type of firms benefit most from active VC involvement. This way, we carve out the mechanisms and implications of the main results. Our analyses show that the main effects are moderated for firms with particularly high ex-ante patenting experience and those for which patenting is decisively less relevant. Hence, investor involvement is most rewarding for firms that can still benefit from external knowledge, such as firms with relatively limited patenting experience but a positive demand for expert input.

Our results have important implications. They provide a differentiated perspective on the role of VCs in the trajectories of their target firms. Highly specialized, experienced VCs can indeed foster innovation across any target firm. Nevertheless, this ability does not apply to all VCs and depends on underlying firm characteristics. From a research perspective, our findings reveal an important explanation for the mixed findings on the effects of VC investments on firms' innovation performance. Specifically, our findings are able to explain both literature that argues in favor and against the treatment effects of VC investors. Based on our conceptual framework and backed by the empirical findings, our analysis emphasizes the importance of considering several accompanying features when interpreting the effects of VC investor involvement on their portfolio firms' activities. Particularly, they emphasize the importance of considering firm- and investor-level differences when evaluating VCs' role in affecting firm performance. In addition to this, our findings entail important managerial implications. As such, they suggest that startups seeking investment need to be aware of the potential (and the limits) of inputs provided by VC investors. These factors may significantly vary, depending on the specific business model and lifecycle stage. From an investor's perspective, our results highlight the need for an effective matching of investors and targets in the market for entrepreneurial financing.

Despite its advantages, our empirical setting is not without limitations. Using large-scale observational data, as we do in this paper, has the advantage of providing generalizable results. Still, while we are confident to provide robust evidence on the main results and mechanisms, it is impossible to fully remove unobserved differences across VC-funded versus non-funded firms. For example, descriptive statistics suggest that firms in the control groups have a similar demand for external financing in the years around the initial investment date. However, our data does not allow us to control for firms' financing demand more explicitly. As a complementary approach to tackle selection concerns, future research may, therefore, need to exploit identifying events or randomized control trials. Alternatively, if the setting permits, one could take advantage of distinguishing between accepted and rejected VC funding applicants. Finally, prior literature (e.g., Zhou *et al.* 2016) shows that other forms of intellectual property, such as trademarks, signal highly relevant capabilities of target firms, too. We thus encourage future research to incorporate these complementary perspectives into their analyses on the importance of VCs for shaping the trajectories of their target firms.

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Tables from the main part

Table 1: Summary statistics

Panel A: Statistics on main variables

	Obs.	Mean	SD	Min.	Q25	Median	Q75	Max.
FirmAge	64,745	9.581	8.573	1	3	7	13	32
Empl	36,951	98.354	288.162	1	5	17	60	2,172
FirmSize	64,768	14.437	2.211	0.693	13.137	14.466	15.783	25.303
AssetGrowth	54,374	0.011	0.033	-0.044	-0.006	0.004	0.021	0.100
DebtRatio	64,661	0.706	0.841	0	0.322	0.592	0.841	1.521
Profitability	49,426	-0.054	0.288	-0.836	-0.105	0.014	0.098	0.351
CashFlow	44,088	-0.003	0.240	-0.649	-0.042	0.051	0.130	0.328
Tangibility	64,768	0.196	0.281	0	0.013	0.062	0.249	1
LogPatFilings	64,768	0.051	0.247	0	0	0	0	4.522
PatFilings	64,768	0.050	0.218	0	0	0	0	1

Panel B: Country and industry distributions

	Obs.	in %
France	2,582	26.89
Great Britain	1,840	19.16
Germany	1,230	12.81
Spain	746	7.77
Netherlands	636	6.62
Sweden	588	6.12
Other EU countries	1,980	20.62
Total	9,602	100.00

	Obs.	in %
Information & communication	2,533	26.38
Manufacturing	1,958	20.39
Scientific & technical activities	1,876	19.54
Wholesale/retail trade	1,100	11.46
Finance & insurance	620	6.46
Admin. & service activities	522	5.44
Other Industries	993	10.34
Total	9,602	100.00

Notes: The table provides the summary statistics for the full sample. Panel A provides the statistics for the key variables used in the analyses. All variables are defined in Table IA1 (Appendix). Panel B displays the country and industry distribution of the sample. Note that we excluded firms located in Luxembourg because its economy primarily comprises financial firms.

Table 2: Cox Regression: pre-VC non-patenting firms (V^0 and N^0)

	Pr(*Patent*)				
	(1)	(2)	(3)	(4)	(5)
VC	1.323***	1.360***	1.452***	2.139***	1.477***
	(0.157)	(0.158)	(0.219)	(0.441)	(0.188)
FirmSize	0.134***	0.145***	0.159***	0.232***	0.183***
	(0.025)	(0.030)	(0.040)	(0.061)	(0.030)
Profitability	-1.107***	-1.115***	-1.646***	-0.326	-1.545***
	(0.364)	(0.393)	(0.472)	(0.847)	(0.328)
CashFlow	-0.494	-0.275	0.247	-1.680*	-0.044
	(0.421)	(0.457)	(0.546)	(0.997)	(0.377)
DebtRatio	-0.390**	-0.263*	-0.245	-0.221	-0.287***
	(0.168)	(0.147)	(0.157)	(0.259)	(0.095)
FirmAge	-0.037***	-0.044***	-0.062***	-0.073***	-0.052***
	(0.008)	(0.009)	(0.018)	(0.016)	(0.010)
Tangibility	-0.231	-0.753***	-1.038**	-1.535**	-0.940**
	(0.220)	(0.289)	(0.432)	(0.672)	(0.279)
Citations:	Any	Any	≥ 1	$\geq Q75$	Any
Country FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
Chi^2	288.46	1,894.06	825.12	1,478.67	125,114
Obs	22,857	22,857	23,315	23,609	23,956

Notes: In this table, we present the results of our semiparametric survival approach. The regression specifications follow Equation (5). All models display Cox regressions which predict the probability of an event of interest at time t, c.p.. The event of interest is the filing of a patent application for the first time (Columns 1 and 2), the filing of a patent application with at least one citation for the first time (Column 3), the filing of a patent application in the top quartile of the citation distribution (Column 4), or the filing of a patent application at any time (Column 5). Specifically, Column (5) allows for multiple failures in order to address the concern that a one-time patent application could be random. The data in Columns 1-4 are set up such that firms drop out of the dataset after the first failure. All regressions include the binary variable VC that equals one for VC-backed startups (V^0) and zero otherwise (i.e., for N^0). Moreover, we add a set of firm characteristics and several fixed effects as indicated in the bottom of the table. All variables are defined in Table IA1 (Appendix). Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 3: Assessing the accelerating Effect: Baseline difference-in-difference estimations

Dependent variables:	*LogPatFilings*			*CitsFilings*	
	(1)	(2)	(3)	(4)	(5)
VC	0.029				
	(0.030)				
Post	-0.102***				
	(0.032)				
VC × Post	0.041	0.054		-0.016	
	(0.042)	(0.038)		(0.044)	
VC × Med-post			0.005		-0.012
			(0.036)		(0.040)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	No	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes
R^2	0.13	0.45	0.45	0.41	0.41
Obs.	4,259	4,259	4,259	4,259	4,259

Notes: The table displays the results of the difference-in-differences approach as described in Section 3.2. The dependent variable is the logarithm of the number of annual patent applications (Columns 1-3) and citation-weighted patent applications (in logs) (Columns 4-5). The regression specifications follow Equation (6). In Column 1, firm- and relative-year fixed effects are omitted. All variables are specified accordingly. Columns 3 and 5 use an alternative specification of the Post-variable, Med-post, which measures the effect of VC investment on patenting in the medium term and is equal to one only for the years 2, 3, and 4 after the initial VC investment. The sample comprises VC-funded firms and their matched counterpart for all years [-3,8] before and after the initial VC investment in a given strata. Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 4: Actual and hypothetical patenting activity for firms without pre-VC patent filings

	Actual	Predicted	Differences in means	Actual	Predicted	Differences in means
	Panel A: *LogPatFilings*					
	VC-funded firms (V^0)			**Comparison group (N^0)**		
t=1	0.037	0.013	-0.025***	0.004	0.020	0.016***
t=2	0.042	0.012	-0.030***	0.007	0.022	0.014***
t=3	0.046	0.012	-0.034***	0.008	0.023	0.014***
t=4	0.053	0.011	-0.043***	0.010	0.024	0.014***
t=5	0.059	0.011	-0.049***	0.009	0.024	0.015***
t=6	0.062	0.011	-0.051***	0.007	0.026	0.019***
t=7	0.077	0.011	-0.067***	0.011	0.028	0.017***
t=8	0.047	0.010	-0.036***	0.011	0.029	0.018***
	Panel B: *CitsFilings*					
	VC-funded firms (V^0)			**Comparison group (N^0)**		
t=1	0.042	0.005	-0.037***	0.004	0.024	0.021***
t=2	0.045	0.005	-0.040***	0.004	0.026	0.023***
t=3	0.049	0.005	-0.044***	0.007	0.027	0.020***
t=4	0.049	0.006	-0.044***	0.008	0.028	0.020***
t=5	0.053	0.006	-0.047***	0.006	0.029	0.023***
t=6	0.056	0.007	-0.049***	0.004	0.031	0.028***
t=7	0.061	0.006	-0.055***	0.005	0.032	0.027***
t=8	0.037	0.006	-0.031***	0.004	0.033	0.029***

Notes: This table presents the results from the second stage of an endogenous switching regression model—the associated "what-if" analysis. The dependent variable in the first stage (see Table IA5, Appendix) is whether a firm receives VC funding in a given year. The dependent variable in the second-stage regression is the logarithm of the number of patent filings or the citation weighted logarithm of total patent filings, respectively. The independent variables in the prediction regressions are the inverse Mills ratio from the first stage and all the independent variables from the semiparametric survival analysis, including the set of fixed effects. The table displays the actual value of the dependent variables, the hypothetical values, and the difference between the two values. Whenever indicated, *, **, and *** denote significance at the 5, 10, and 0.1 percent levels, respectively.

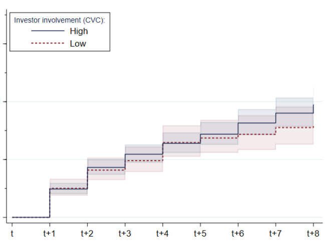
Table 5: VC involvement and the enabling Effect

Panel A: Cox estimations

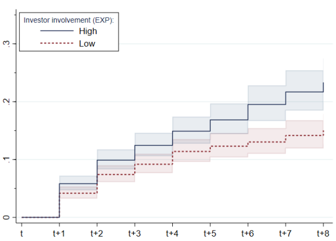
	$Pr(Patent)$					
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Invo^{high}	-0.016	-0.229	0.858			
	(0.350)	(0.327)	(0.505)			
VC	1.320***	1.434***	1.198***			
	(0.293)	(0.239)	(0.184)			
Invo^{high}	-0.189	0.305	-0.461	-0.219	0.063	0.433**
	(0.328)	(0.307)	(0.483)	(0.150)	(0.135)	(0.152)
Invo^{high} definition:	CVC	EXP	REP	CVC	EXP	REP
Sample:	all ($V0$ and N^0)			V^0 only		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	1,113.04	1,141.12	1,142.89	898.20	916.71	921.24
Obs.	17,304	17,304	17,304	8,880	8,880	8,880

Panel B: Additional effect of investor involvement on the enabling effect (V^0 only)

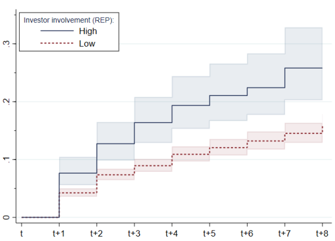
Invo^{high}: CVC



Invo^{high}: EXP



Invo^{high}: REP



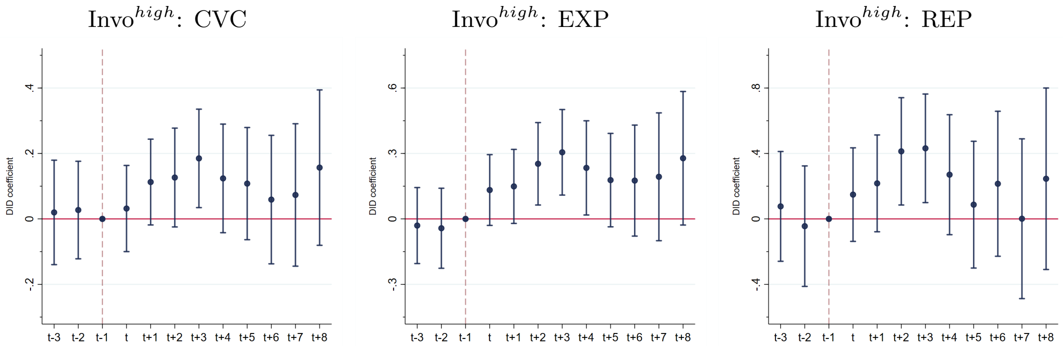
Notes: Panel A shows the results of our extended semiparametric survival approach as defined in Equation (11). All models display Cox regressions which predict the probability of a patent application at time t, c.p.. All regressions include the indicator Invo_m^{high} with m being either one of the three VC characteristics defined as measuring highly involved investors ($\in [CVC, EXP, REP]$) as defined in Section 5.1. Estimations in Columns 1-3 also include the interaction term of the Invo^{high}-dummy with the VC indicator. Columns 4-6 repeat the same estimations but for the subsample of VC-backed firms. Hence, the VC indicator and the interaction terms drop due to perfect multicollinearity. Moreover, we include the same set of firm characteristics and fixed effects as in our baseline Cox regressions. Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Panel B displays the Kaplan-Meier failure estimates (hazard rates) displaying the unconditional probability of a VC-backed startup to file a patent. Each of the three graphs plots the probability for startups with a highly involved (straight line) and low involved investor (dashed line), respectively. The shaded areas around the lines mark the 95 percent confidence intervals.

Table 6: VC involvement and the accelerating Effect

Panel A: Investor involvement and the accelerating effect

Dep. variable:	*LogPatFilings*					
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Post × $Invo^{high}$	0.136	0.211***	0.207**	0.226***	0.131	0.269***
	(0.086)	(0.080)	(0.087)	(0.080)	(0.130)	(0.104)
VC × Post	-0.031	-0.114*	-0.033	-0.065	0.031	-0.018
	(0.066)	(0.064)	(0.055)	(0.049)	(0.045)	(0.043)
Post × $Invo^{high}$	-0.046	-0.014	0.001	-0.070	-0.063	-0.035
	(0.053)	(0.052)	(0.057)	(0.048)	(0.081)	(0.057)
$Invo^{high}$ definition:	*CVC*		*EXP*		*REP*	
Post definition:	Post	Med-post	Post	Med-post	Post	Med-post
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.46	0.46	0.46	0.46	0.46	0.46
Obs.	3,741	3,741	3,713	3,713	3,741	3,741

Panel B: Coefficient plots: Event study graphs



Notes: This table provides the estimation results on the effect of VC involvement in the context of the accelerating effect. Panel A displays the results for the estimates of Equation (12) that use different definitions of high VC involvement. In Columns 1, 3, and 5, the *Post*-dummy is equal to one for all years after initial VC investment and zero otherwise. In Columns 2, 4, and 6, the *Post*-dummy is equal to one only for the years 2, 3, and 4 after initial investment, that is, as defined in Table IA1. The dependent variables are an indicator equal to one if the investors are either CVCs (Columns 1-2), or are highly experienced (EXP; Columns 3-4) or have a high reputation (REP; Columns 5-6), as defined in Section 5.1. Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Panel B displays the dynamic treatment effect with plots of the DID coefficients from event study type regressions that interact year dummies with the VC indicator. The three categories correspond to the definitions of CVC, EXP, and REP from Columns 1-2, 3-4, and 5-6 in Panel A, respectively. Years are denoted as the strata-specific relative years to the initial VC investment when using the final year prior to the VC investment as the reference year. Whiskers span the 95 percent confidence intervals.

Table 7: Who benefits from VC involvement? Different levels of patenting experience

Panel A: Investor involvement and ex-ante patenting activities

Dep. variable:	*LogPatFilings*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VC × Med-post × $Invo^{high}$	0.379***	0.275**	0.391**	0.110	0.164	0.258	0.129	0.178	0.120
	(0.130)	(0.129)	(0.185)	(0.133)	(0.150)	(0.220)	(0.167)	(0.153)	(0.185)
Med-post × $Invo^{high}$	-0.018	-0.069	-0.106	0.129	0.020	0.015	-0.072	-0.090	-0.098
	(0.111)	(0.081)	(0.107)	(0.100)	(0.107)	(0.119)	(0.113)	(0.089)	(0.100)
VC × Med-post	-0.199*	-0.042	0.010	-0.074	-0.060	-0.046	-0.122	-0.104	-0.050
	(0.110)	(0.080)	(0.070)	(0.094)	(0.076)	(0.073)	(0.144)	(0.091)	(0.081)
$Invo^{high}$ definition:	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*
Pre-VC experience:									
Quality-weighted patent stock:	Small			Medium			Large		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.54	0.54	0.54	0.44	0.45	0.44	0.51	0.51	0.51
Obs.	1,178	1,176	1,178	1,094	1,082	1,094	1,164	1,154	1,164

Panel B: Sector-level patenting intensity as measure of experience

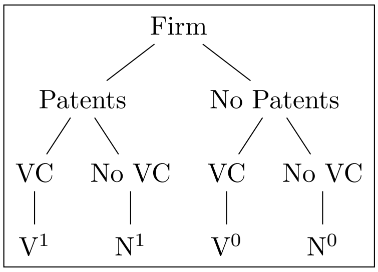
Dep. variable:	*LogPatFilings*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VC × Med-post × $Invo^{high}$	0.035	0.025	0.078	0.397**	0.437***	0.551**	0.180	0.238*	0.240
	(0.116)	(0.124)	(0.128)	(0.159)	(0.144)	(0.258)	(0.133)	(0.139)	(0.194)
Med-post × $Invo^{high}$	0.065	0.048	0.025	-0.129	-0.122	0.051	0.180	-0.093	-0.054
	(0.070)	(0.068)	(0.084)	(0.095)	(0.085)	(0.136)	(0.133)	(0.083)	(0.122)
VC × Med-post	0.005	0.006	0.006	-0.108	-0.014	0.096	-0.159	-0.118	-0.070
	(0.075)	(0.070)	(0.071)	(0.138)	(0.082)	(0.076)	(0.111)	(0.077)	(0.072)
$Invo^{high}$ definition:	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*
Pre-VC experience:									
Industry-level patenting intensity:	Low			Medium			High		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.56	0.56	0.56	0.48	0.49	0.49	0.50	0.50	0.50
Obs.	903	903	903	1,000	988	1,000	1,620	1,608	1,620

Notes: This table displays heterogeneous treatment effects, using split sample regressions that distinguish between firms' ex-ante patenting expertise. Panel A repeats the augmented accelerating effect regressions as defined in Equation (12) for three different subsamples, depending on firms' pre-VC patenting stock size. We measure patent stock size as a quality-weighted count of firms active patents in the year before the initial VC investment and separate firms in the bottom (Columns 1-3), medium (Columns 4-6), and top (Columns 7-9) tercile of the patent stock distribution. Respective estimations in Columns 1-3, 4-6, and 7-9 distinguish the three measures of high VC involvement, CVC, experience, and reputation, as in Columns 2, 4, and 6 of Table 6. Panel B repeats this analysis and is structured equivalent to before, using an alternative measure of patenting expertise. Here, we differentiate firms according to their sector-specific patenting intensity. To classify industries, we follow the EPO-EUIPO report (2022) and classify firms as *low* patenting intensive if the operate in sectors that are not considered as patenting intensive in the report. Firms that operate in patenting intensive sectors that are not listed in the top 50 as defined by the EPO-EUIPO report are considered as *medium* patenting intensive (Columns 4-6), and firms operating in any of the top 50 most patenting intensive sectors are considered as *high* patenting intensive (Columns 7-9). In both panels, standard errors are clustered at the firm level and, whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels.

Figures from the main part

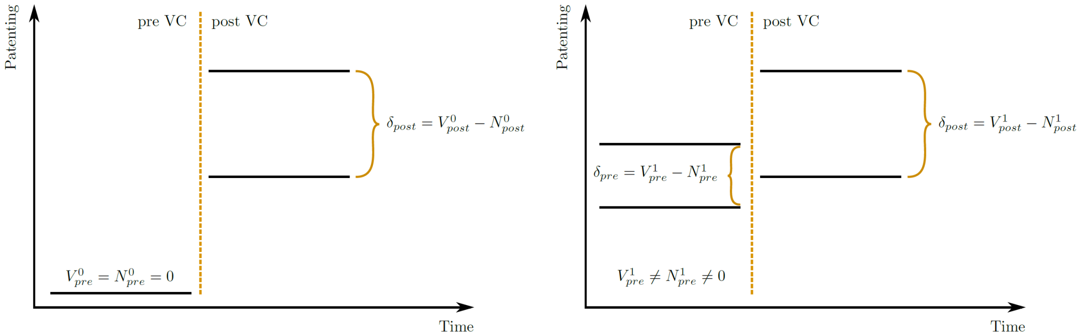
Figure 1: Graphical illustrations of the conceptual framework

Panel A: Defining different firm types regarding patenting and VC investments



	VC funding	No VC funding
Patents	V^1	N^1
No Patents	V^0	N^0

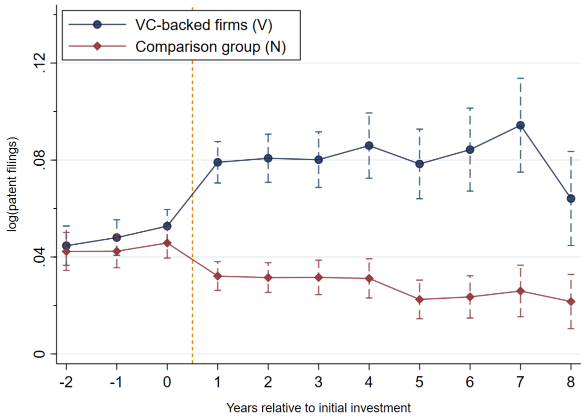
Panel B: Illustrating the Enabling and Accelerating Effects of VC Investments



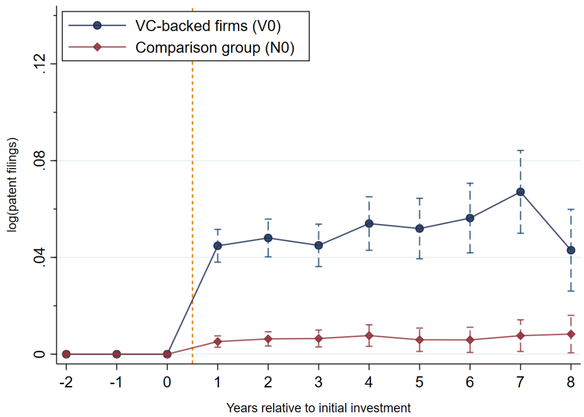
Notes: These Panels illustrate conceptually the methodological framework of our empirical strategy. Panel A illustrates graphically how we distinguish the different firm types relevant to our conceptual framework, as outlined in section 2.2. Panel B is a graphical illustration of the two main effects, the enabling and the accelerating effect of VCs, as described in Section 2.2.

Figure 2: Mean plots: Average patent filings relative to the VC investment date

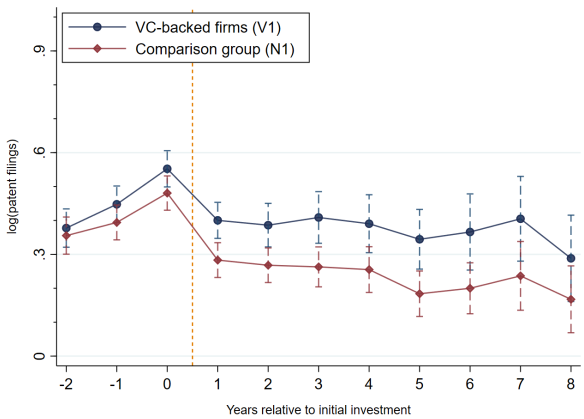
Panel A: All firms



Panel B: Pre-VC non-patenting firms

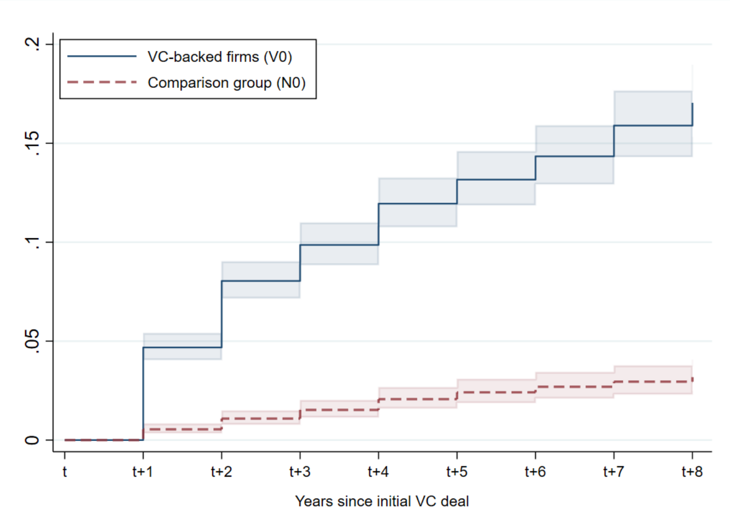


Panel C: Pre-VC patenting firms



Notes:Panel A shows a comparison of the average VC-funded firms (V) and their non-VC-funded partners (N), irrespective of their pre-VC patent activities. Panels B and C show the potential enabling and accelerating effects as defined in 2.2. We differentiate between firms with and without patent filings prior to the initial VC round. First, Panel B shows the results for pre-VC non-patenting firms (V^0 and N^0) while Panel C compares the two groups of pre-VC patenting firms (V^1 and N^1). All Panels display the logarithm of the number of patent applications each year.

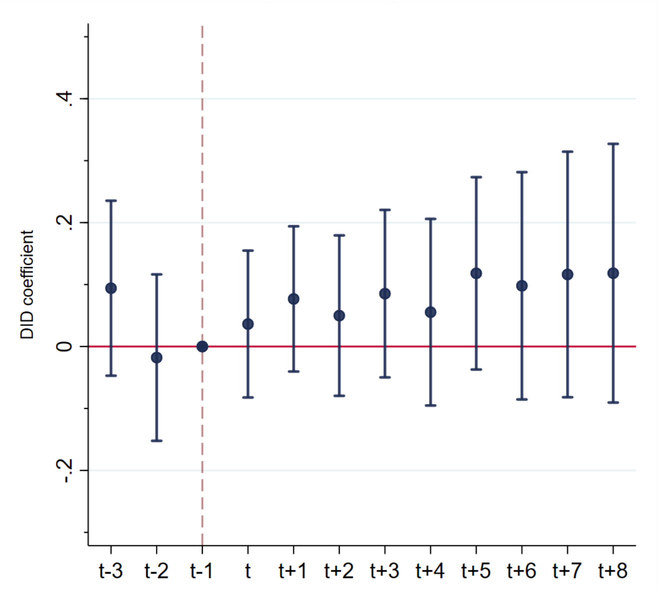
Figure 3: Enabling effect: The probability (cumulative hazard) of patenting for pre-VC non-patenting firms



Notes: This graph displays the Nelson-Aalen cumulative hazard estimates for the treatment versus the control group, estimating. The treatment group comprises firms that have received VC funding but did not file patents before the initial round of funding, while the non-funded firms comprise the control group. Firms drop out of the dataset right after they filed their first patent.

Figure 4: Accelerating effect of VC investment: Event study regressions

$LogPatFilings$



Notes: The figure shows the plot of coefficients for the event study type regression from Equation (10). The dependent variable in Panel A is the logarithm of patent filings as defined in Table IA1 (Appendix). The coefficient plots display the DID coefficients that interact year dummies with the VC indicator. Years are denoted as the strata-specific relative years to the initial VC investment. Whiskers span the 95 percent confidence intervals.

FOR ONLINE PUBLICATION (APPENDICES):

Internet Appendix A : Tables

Table IA1: List of variables

Key variables:	
VC	Dummy equals one if the firm receives venture capital at any point in time and zero for matched comparison group firms.
Post	Dummy equals one for any firm-specific year t after the initial VC investment (within matched strata) and zero otherwise.
Med-post	Dummy equals one for any firm-specific years T ($\in$ [2,4]) after the initial VC investment(within matched strata) and zero otherwise.
LogPatFilings	Logarithm of total patent filings within a year (main dep. variable).
Prob(Patent)	Instantaneous probability to file for a patent or a high quality patent in t.
Pre^S	Dummy equals one for any firm-specific year S ($\in$ [-3,-2]) before the initial VC investment (within matched strata) and zero otherwise.
$Post^S$	Dummy equals one for any firm-specific year S ($\in$ [0,8]) after the initial VC investment (within matched strata) and zero otherwise.
$Invo^{high}$	Dummy equals one for any VC-funded firm that is financed by a highly-involved VC specified as indicated by any of the three criteria, CVC, EXP, or REP, as defined below, and zero otherwise.
CVC	Dummy equals one for any target firm that is funded by a corporate venture capitalist. The baseline specification classifies VCs as CVCs if it acts both as investor and as organization in the Crunchbase database, and zero otherwise.
EXP	Dummy equals one for any target firm (or its matched couterpart) that is backed by a VC with an above median number of deals the investor has previously participated in, and zero otherwise.
REP	Dummy equals one for any target firm that is backed by a VC with high reputation as measured by the accumulated dollar market value of all targets that successfully exited via IPO or acquisition, normalized using the total annual aggregated IPO and M&A market values in Europe since 1980.
Main control variables (Orbis code):	
DebtRatio	Total-debt-to-asset ratio (`loan`+`cred`+`ltdb`)/`toas`.
FirmSize	Logarithm of total assets (`toas`).
Profitability	Return on assets; earnings before interest and taxes (`ebit`) divided by total assets (`toas`).
CashFlow	Total cash flow (`cf`) scaled by total assets (`toas`).
Tangibility	Share of fixed tangible assets (`tfas`) over total assets (`toas`).
FirmAge	Time (full years) since incorporation date (`Date_of_incorporation`) and the balance sheet reporting date (`Closing_date`).

(*continued on next page*)

Table IA1: List of variables (*continued*)

Other variables (Orbis code):	
AssetGrowth	Year-to-year growth in total assets (`D.toas/L.toas`).
CurrentRatio	Liquidity risk; total current assets (`cuas`) over current liabilities (`culi`).
PatFilings	Dummy equals one for any firm-year in which a firm filed at least one patent and zero otherwise.
CitsFilings	Logarithm of 1+citations received by patent over patent filing, with citations counted within the first five years after filing.
AvgCitsFilings	Average number of citations received by patent over patent filing, with citations counted within the first five years after filing.
RecencyTop1	Dummy equals one if firms file at least one patent in the top 1 percentile of the recency distribution; where recency is defined as the average time lapsed between the filing of the focal patent and the referenced patents.
RecencyTop25	Dummy equals one if firms file at least one patent in the top quartile of the recency distribution and zero otherwise.
OriginalityAvg	The average originality score of patents filed within a given year; originality refers to patent breadth as defined in Hall *et al.* (2001).
OriginalityMax	The maximum originality score of patents filed within a given year.
Empl	The total number of employees (`empl`) at the end of the reporting period.
Synd	Dummy equals one for firms whose initial VC investment round included more than one investor and zero otherwise.
$PatIntensity^S$	Dummy equals one for all firms that operate in sector S and zero otherwise, where $S \in [lo, med, hi]$ indicates low, medium or high patenting intensity. These intensities are determined according to the industry classifications suggested in EPO-EUIPO (2022). For the top-50 most intensive sectors $PatIntensity^{hi}$ equals one, for the 97 other patenting intensive sectors $PatIntensity^{med}$ equals one, and, for all industries not classified in the report, $PatIntensity^{lo}$ equals one.
LogPatFilings_Stock	The accumulated patent stock measured in past patent filings (in logs) using different discount rates as described in Table IA9.
CitsFilings_Stock	The accumulated, citation-weighted patent stock, with discount rates for $LogPatFilings\_Stock$.
logSales	The natural logarithm of firms' total sales (`sale`).
logInvestments	The natural logarithm of firms' total investments, including capital expenses (`capx`) and operating expenses (`oexp`).
RZscore	Following Rajan and Zingales (1998), these firm-level scores are equal to the fraction of investments (`capx`) not covered by cash flows (`cf`), defined as (`capx` − `cf`)/`capx`.

Table IA2: Comparing matched sample groups at different lifecycle stages

Panel A: Firms *with* and *without* pre-VC patent filings *before* the initial investment

	VC-funded (V/N)		Differences in means	VC-funded (V/N)		Differences in means
	V^1	N^1		V^0	N^0	
FirmSize	13.924	14.036	-0.113	13.689	13.657	0.032
FirmAge	7.814	7.790	0.024	7.689	7.673	0.016
AssetGrowth	1.117	1.102	0.015	1.110	1.107	0.003
CurrentRatio	1.968	1.953	0.015	1.728	1.775	-0.047
PatFilings	0.805	0.699	0.106	0	0	0
LogPatFilings	0.670	0.613	0.056	.	.	.
RecencyTop1	0.044	0.016	0.027*	.	.	.
RecencyTop25	0.566	0.519	0.047	.	.	.
OriginalityAvg	0.337	0.350	-0.013	.	.	.
OriginalityMax	0.382	0.391	-0.009	.	.	.

Panel B: Survival rates *after* the initial investment

	VC-backed firms (V)	Comparison group (N)	Differences in means	(t-value)
With pre-VC filings (V^1 vs. N^1)				
Mean nbr. of post-investment observations:	4.945	4.921	0.024	(0.142)
Share of firms surviving first 2 years:	0.253	0.259	-0.006	(0.185)
Share of firms surviving first 4 years:	0.498	0.499	-0.001	(0.033)
Without pre-VC filings (V^0 vs. N^0)				
Mean nbr. of post-investment observations:	5.023	4.979	0.045	(0.775)
Share of firms surviving first 2 years:	0.274	0.268	0.006	(0.609)
Share of firms surviving first 4 years:	0.498	0.494	0.004	(0.354)

Panel C: Investment statistics of pre-VC patenting (V^1) and non-patenting (V^0) firms

	V^1	V^0	Differences in means
Funding received: first round	2.902	4.931	-2.029
Funding received: all rounds	5.804	6.552	-0.747
Number of VC deals	1.793	1.540	0.253***

Notes: The table provides the summary statistics for financial and patenting variables for the five pre-VC years. The table shows a comparison of the two treatment and control group firms as defined in Section 2.2. Specifically, Panel A compares firms with (V^1, N^1) and without (V^0, N^0) patent activities prior to the initial VC investment using the average of the two pre-VC investment years. The panel presents the mean values for a set of covariates, including the main firm-level control variables and patenting measures as defined in Table IA1 (Appendix). Panel B displays statistics on startups survival rates, distinguishing the same four subgroups. Our data does not consistently report insolvencies such that we compute firms survival using information on whether we observe firms two or four years after the initial VC investment date, respectively. Panel C provides the statistics for VC- and IPO-related variables for the sample firms that eventually received VC funding by comparing pre-patenting and non-patenting firms as defined in the Section 2.2. It displays information on the deal sizes in the first round and overall rounds (in million Euros) and the total number of deals made. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA3: Robustness tests: the Enabling Effect

	$Pr(Patent)$											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VC	1.315***	1.487***	1.343***	1.817***	0.871***	0.773***	2.027***	1.630***	1.762***	1.025***	1.782***	0.967***
	(0.175)	(0.366)	(0.174)	(0.243)	(0.216)	(0.207)	(0.374)	(0.351)	(0.355)	(0.205)	(0.256)	(0.200)
I(Φ)			-0.142			-0.507*			0.058			-0.381
			(0.342)			(0.303)			(0.463)			(0.283)
VC × I(Φ)			0.068			1.118***			0.016			0.842**
			(0.361)			(0.307)			(0.488)			(0.304)
Sample:	Short	Long	Any	<4 years	>4 years	Any	Small	Large	Any	No	Yes	Any
Sample criteria (factor Φ):	Survivorship			Age at first deal			First deal size			Follow-on investments		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	1,015.18	6,670.93	1,907.85	469.51	1,897.98	2,183.33	2,917.87	92,074.53	1,132.08	101,824.81	2,554.91	2,021.71
Obs.	18,476	4,381	22,857	10,968	11,889	22,857	5,595	5,687	11,282	12,451	10,023	22,474

Notes: This table presents robustness tests on the baseline enabling effect estimations. Specifically, it tests for differences in the main results with respect to startup performance, regarding survival (Columns 1-3), age at first investment (Columns 4-6), deal size (Columns 7-9), and follow-on investments (Columns 10-12). Specifically, Colums 1 and 2 use the same specification as in Column 2 of Table 2, only here the sample is split according to startups that did not survive (Column 1) and those that survived (Column 2) at least the first three years after the initial VC deal (i.e., we do not or do observe them in year t=4). Accordingly, Columns 4 and 5 separate targets that are at most four years old or at least four years old, respectively, with four years being the median age of all sample firms at the time of the first VC funding. Columns 7 and 8 are split across firms with below and above the medium initial deal size, and Columns 10 and 11 are split across firms that did not and those that did raise another follow-on VC round. Columns 3, 6, 9, and 12 apply the same logic as the split sample regressions but use interaction specifications, i.e., they use the full sample and include a dummy variable, I(Φ), and its interaction with the VC-indicator. I(Φ) equals one for firms that did not survive the first four years (Column 3), are not older than four years at first funding (Column 6) , have a large (above median) first funding round (Column 9), or obtained at least one follow-on VC deal (Column 12), and zero otherwise. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA4: Robustness tests: the Accelerating Effect

	$Pr(Patent)$											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VC × Post	-0.020	0.092*	0.095*	0.035	-0.022	-0.024	0.042	0.097	0.050	0.020	0.079	0.026
	(0.060)	(0.049)	(0.049)	(0.050)	(0.052)	(0.052)	(0.064)	(0.077)	(0.064)	(0.050)	(0.057)	(0.052)
I(Φ) × Post			0.068			-0.060			-0.019			-0.047
			(0.058)			(0.045)			(0.463)			(0.052)
VC × I(Φ) × Post			-0.130			0.055			0.045			0.059
			(0.079)			(0.072)			(0.102)			(0.079)
Sample:	Short	Long	Any	<4 years	>4 years	Any	Small	Large	Any	No	Yes	Any
Sample criteria (factor Φ):	Survivorship			Age at first deal			First deal size			Follow-on investments		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.47	0.48	0.45	0.48	0.48	0.45	0.47	0.49	0.47	0.46	0.49	0.45
Obs.	1,287	2,902	4,198	2,148	2,109	4,259	1,129	1,433	2,563	2,023	2,164	4,198

Notes: This table presents robustness tests on the baseline accelerating effect estimations, using the specifications equivalent to Table IA4. Only here, the reference is the accelerating effect estimations, i.e., Column 2 of Table 3. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA5: Heckman-type estimates of the Switching Regressions with Endogenous Switching

Panel A: First stage results

Dep. variable:	Pr(VC)		
	(1)	(2)	(3)
$FirmSize$	0.119***	0.113***	0.099***
	(0.010)	(0.034)	(0.033)
$Profitability$	-0.922***	-0.673	-0.612
	(0.130)	(0.415)	(0.413)
$CashFlow$	-0.966***	-0.429	-0.378
	(0.153)	(0.478)	(0.476)
$DebtRatio$	-0.395***	-0.267***	-0.239***
	(0.029)	(0.072)	(0.070)
$FirmAge$	-0.013***	-0.006	-0.003
	(0.002)	(0.005)	(0.005)
$Tangibility$	-0.587***	-0.041	-0.060
	(0.069)	(0.276)	(0.272)
$CitsFilings$			0.178***
			(0.057)
$OriginalityAvg$			0.220
			(0.204)
Ex-ante patenters	No (V^0, N^0)	Yes (V^1, N^1)	
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Wald Chi^2	1,320	74.15	93.40
Obs.	26,824	2,982	2,982
Groups	6,092	634	634

Panel B: Second stage estimates on the inverse Mills ratio

Dep. variable:	$LogPatFilings$		$CitsFilings$		$LogPatFilings$	
	(1)	(2)	(3)	(4)	(5)	(6)
$lambda$	0.230***	0.275*	0.197***	0.065*	2.330*	2.376*
	(0.075)	(0.160)	(0.093)	(0.039)	(1.309)	(1.376)
Ex-ante patenters	No (V^0)	No (N^0)	No (V^0)	No (N^0)	Yes (V^1)	Yes (N^1)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.03	0.006	0.002	0.09	0.13
Obs.	20,930	18,760	20,930	18,760	2,202	2,111

Notes: Panel A displays the first-stage results of switching regressions for ex-ante non-patenting (Column 1) and patenting (Columns 2-3) firms. The dependent variable is the VC-indicator, which equals one if a firm eventually obtains VC funding and zero otherwise. The regressions additionally include a set of fixed effects as indicated in the bottom of the table. Column 3 includes patent quality variables as additional controls. All variables are specified as before. Panel B displays the coefficients of the inverse Mills ratios (*lambda*) for the second stage regressions that are used to calculate the hypothetical patenting activities in Tables 4 and IA6 (Appendix). Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA6: Actual and hypothetical patent filings for pre-VC patent filing firms

	Actual	Predicted	Differences in means	Actual	Predicted	Differences in means
	LogPatFilings					
	VC-funded firms (V^1)			Comparison group (N^1)		
t=1	0.392	0.369	-0.023	0.295	0.436	0.141***
t=2	0.363	0.360	-0.003	0.273	0.421	0.147***
t=3	0.396	0.356	-0.040	0.268	0.418	0.150**
t=4	0.412	0.257	-0.056	0.293	0.435	0.142*
t=5	0.397	0.345	-0.052	0.206	0.440	0.234**
t=6	0.401	0.284	-0.117	0.229	0.340	0.111**
t=7	0.425	0.269	-0.157*	0.287	0.321	0.034
t=8	0.315	0.224	-0.091	0.176	0.299	0.123*

Notes: This table presents the results from the prediction stage of an endogenous switching regression model—the associated "what-if" analysis—for firms with pre-VC patent filings. The regressions are specified equivalent to those in Table 4, only here they are estimated for the subset of pre-VC patenting firms. Hence, the dependent variable in the first stage is a dummy equal to one for firms that receive VC funding in a given year or zero otherwise. The dependent variable in the second-stage regression is the logarithm of the number of patent filings (*LogPatFilings*). The first and second stage results are displayed in Table IA5 (Appendix). The table presents the actual number of patent filings, the hypothetical value, and the difference between the two values. Whenever indicated, *, **, and *** denote significance at the 5, 10, and 0.1 percent levels, respectively.

Table IA7: Robustness tests: investor involvement and the enabling effect

Panel A: The probability of filing a high quality patent

	$Pr(Patent^{hq})$					
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Invo^{high}	0.104	0.723	1.450			
	(0.502)	(0.454)	(0.772)			
VC	1.383**	1.138***	1.256***			
	(0.443)	(0.293)	(0.248)			
Invo^{high}	-0.062	0.030	-0.452	0.267	-0.967	0.516**
	(0.479)	(0.200)	(0.427)	(0.174)	(0.749)	(0.188)
Invo^{high} definition:	CVC	EXP	REP	CVC	EXP	REP
Sample:	all (V^0 and N^0)			V^0 only		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	725.21	732.47	94,469.00	115,315.64	569.01	88,748.98
Obs.	17,680	17,680	17,680	9,181	9,181	9,181

Panel B: Testing alternative definitions of investor reputation

	$Pr(Patent)$					
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Invo^{high}	0.463	0.458	0.957			
	(0.364)	(1.043)	(0.559)			
VC	1.182***	1.301***	1.198***			
	(0.200)	(0.177)	(0.182)			
Invo^{high}	-0.229	-0.549	-0.705	0.260	-0.027	0.277
	(0.342)	(1.005)	(0.535)	(0.139)	(0.314)	(0.157)
Invo^{high} definition:	REP_{nbrs}	REP_{world}	REP_{US}	REP_{nbrs}	REP_{world}	REP_{US}
Sample:	all (V^0 and N^0)			V^0 only		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	1,143.30	1,126.94	95,134.39	936.42	910.73	913.61
Obs.	17,304	17,304	17,304	8,880	8,880	8,880

(*continued on next page*)

Table IA7: Robustness tests (*continued*)

Panel C: Testing for survivorship effects

	$Pr(Patent)$					
	(1)	(2)	(3)	(4)	(5)	(6)
VC	1.365***	1.444***	1.188***	1.277***	1.341***	1.109***
	(0.303)	(0.246)	(0.187)	(0.330)	(0.260)	(0.200)
Invo^{high}	-0.166	0.308	-0.675	-0.106	0.269	-0.818
	(0.340)	(0.315)	(0.534)	(0.368)	(0.341)	(0.611)
VC × Invo^{high}	-0.065	-0.227	1.050	-0.017	-0.138	1.237*
	(0.360)	(0.335)	(0.555)	(0.391)	(0.363)	(0.630)
Invo^{high} definition:	CVC	EXP	REP	CVC	EXP	REP
Sample:	survivors until $t > 2$			survivors until $t > 4$		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	766.54	777.35	96,627	706.87	720.14	721.05
Obs.	16,621	16,621	16,621	13,925	13,925	13,925

Panel D: Syndication and the enabling effect

Dependent variable:	$Pr(Patent)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VC	2.142***	1.727***	1.344***	1.092***	1.352***	1.138***	1.137***
	(0.746)	(0.544)	(0.318)	(0.322)	(0.269)	(0.228)	(0.208)
Invo^{high}	0.526	0.800	-1.354	-0.363	0.168	0.087	
	(0.782)	(0.617)	(1.043)	(0.381)	(0.377)	(0.570)	
VC × Invo^{high}	-0.620	-0.088	1.923*	0.060	-0.590	0.020	
	(0.815)	(0.641)	(1.066)	(0.404)	(0.406)	(0.613)	
$Synd$							-0.466
							(0.328)
VC × $Synd$							0.488
							(0.346)
Invo^{high} definition:	CVC	EXP	REP	CVC	EXP	REP	-
Sample ($Synd$):	Syndicated first deal			No syndication			Any
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	1,786.85	1,925.17	1,773.84	768.62	120,741	772.52	1,136.36
Obs.	6,986	6,986	6,986	10,318	10,318	10,318	17,304

Notes: This table displays the results on robustness tests that use different variants of the augmented enabling effect estimations, defined in Equation (11). In Panel A, the underlying estimations are equivalent to those displayed in Panel A of Table 5, only here the dependent variable is an quality-based patent indicator that is equal to one only for patents that receive at least one citation. In Panel B, the regressions are equivalent to those in Columns 3 and 6 of Table 5, but they use different variants of the reputation measure. Standard errors are clustered at the firm level. Reputation is measured as the investors' number (instead of the market value) of successful exists as a share of the total number of exits in Europe, REP_{nbrs} (Columns 1 and 4) or the reputation measured by exits as a fraction of accumulated exits worldwide (Columns 2 and 5) or in the US (Columns 3 and 6). Panel C repeats the estimations from Columns 1-3 of Table 5 for the subsample of firms that survive at least for the first two (Columns 1-3) or four years (Columns 4-6) after the initial VC funding. Panel D is equivalently structured but distinguishes firms whose initial VC investment came from multiple investors (Columns 1-3) or single investors (Columns 4-6). Moreover, the regression in Column 7 is similar to the augmented enabling effect estimations as defined in Equation (11) but uses the indicator $Synd$ instead of $Invo^{high}$. $Synd$ is equal to one for firms whose initial VC investment came from multiple investors and zero otherwise. Standard errors are clustered at the firm level. *, **, and *** denote significance at the 10, 5, and 1 percent levels.

Table IA8: The enabling effect: Distinguishing first investment characteristics

Panel A: The size of the first VC deal and the enabling effect

	$Pr(Patent)$					
	(1)	(2)	(3)	(4)	(5)	(6)
VC	1.385***	1.523***	1.220***	1.193	1.306*	1.296***
	(0.319)	(0.270)	(0.216)	(0.785)	(0.554)	(0.387)
Invo^{high}	-0.133	0.532	-0.147	-0.283	-0.058	-0.524
	(0.372)	(0.352)	(0.615)	(0.757)	(0.660)	(0.794)
VC $\times$ Invo^{high}	-0.240	-0.642	0.274	0.493	0.480	1.208
	(0.395)	(0.376)	(0.643)	(0.879)	(0.718)	(0.860)
Invo^{high} definition:	CVC	EXP	REP	CVC	EXP	REP
Investment size:	Small deal ($< Q50$)			Large deal ($> Q50$)		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	98,867.62	1,614.75	1,598.15	1,712.61	1,449.14	62,163.33
Obs.	12,487	12,487	12,487	4,817	4,817	4,817

Panel B: Plausibility test: follow-on investments

	$Pr(Patent)$					
	(1)	(2)	(3)	(4)	(5)	(6)
VC	3.242**	2.479***	1.864***	0.828**	0.973***	0.711**
	(1.020)	(0.525)	(0.314)	(0.318)	(0.277)	(0.232)
Invo^{high}	1.123	0.901	-0.042	-0.137	0.466	-0.330
	1.043)	(0.583)	(0.580)	(0.384)	(0.409)	(1.012)
VC $\times$ Invo^{high}	-1.494	-0.774	0.402	-0.241	-0.843	1.174
	(1.048)	(0.596)	(0.605)	(0.437)	(0.468)	(0.860)
Invo^{high} definition:	CVC	EXP	REP	CVC	EXP	REP
Sample:	With follow-on investment			Without follow-on investment		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	1,733.54	117,745.89	114,874.90	680.76	688.63	692.33
Obs.	8,831	8,831	8,831	8,473	8,473	8,473

Notes: This table presents a set of estimations that test the robustness of the enabling effect in the context of VC involvement, using specifications as defined in Equation (11). In Panel A, the estimations test for differences in the enabling effect according to the size of the first VC deal. Regressions in Columns 1-3 and 4-6 are specified equivalent to Columns 1-3 in Table 5. Only here, the sample are subsets of firms with below (Columns 1-3) or above (Columns 4-6) median sized first VC investment rounds. Below, includes those firms with missing deal size information. In Panel B, the estimations test for differences in the accelerating effect depending on whether firms obtained follow-on investments, using the same setup as in Panel A. Only here, the sample are subsets of firms with (Columns 1-3) or without (Columns 4-6) at least one follow-on VC investment round. Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA9: Investor involvement and the Accelerating Effect: varying dependent variables

Panel A: Citation weighted patent filings as dependent variable

Dep. variable:	*CitsFilings*					
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Post × Invo^{high}	0.063	0.112	0.221**	0.164*	0.005	0.384***
	(0.092)	(0.089)	(0.103)	(0.086)	(0.154)	(0.120)
VC × Post	-0.079	-0.087	-0.133**	-0.077	-0.034	-0.077*
	(0.065)	(0.071)	(0.055)	(0.056)	(0.052)	(0.045)
Post × Invo^{high}	-0.083	-0.055	-0.065	-0.134**	-0.139	-0.125
	(0.054)	(0.062)	(0.064)	(0.059)	(0.102)	(0.089)
Invo^{high} definition:	*CVC*		*EXP*		*REP*	
Post definition:	Post	Med-post	Post	Med-post	Post	Med-post
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.41	0.41	0.42	0.42	0.41	0.42
Obs.	3,560	3,560	3,560	3,560	3,560	3,560

Panel B: Patent Originality as dependent variable

Dep. variable:	*OriginalityAvg*					
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Post × Invo^{high}	0.029	0.021	0.051	0.059**	-0.016	0.087**
	(0.030)	(0.025)	(0.031)	(0.028)	(0.049)	(0.042)
VC × Post	-0.008	-0.114*	-0.012	-0.065	0.015	-0.018
	(0.023)	(0.064)	(0.019)	(0.049)	(0.016)	(0.043)
Post × Invo^{high}	-0.001	0.026	-0.020	-0.043**	0.003	-0.029
	(0.021)	(0.018)	(0.022)	(0.020)	(0.038)	(0.032)
Invo^{high} definition:	*CVC*		*EXP*		*REP*	
Post definition:	Post	Med-post	Post	Med-post	Post	Med-post
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.35	0.35	0.35	0.35	0.35	0.35
Obs.	3,560	3,560	3,536	3,536	3,560	3,560

(*continued on next page*)

Table IA9: Robustness tests (*continued*)

Panel C: Patent stock (discounted) as dependent variable

Dep. variable:	*LogPatFilings_Stock*			*CitsFilings_Stock*		
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Med-post × REP	0.234***	0.220***	0.202***	0.352**	0.350**	0.290**
	(0.070)	(0.066)	(0.083)	(0.141)	(0.143)	(0.138)
VC × Med-post	-0.012	-0.011	-0.007	0.054	0.057	0.065
	(0.38)	(0.037)	(0.036)	(0.059)	(0.060)	(0.059)
Med-post × REP	-0.075	-0.069	-0.060	-0.111	-0.109	-0.079
	(0.049)	(0.047)	(0.044)	(0.079)	(0.081)	(0.080)
Patent stock discount rate:	15%	0.5/8yrs.	none	15%	0.5/8yrs.	none
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.82	0.84	0.87	0.85	0.85	0.88
Obs.	3,560	3,560	3,560	3,560	3,560	3,560

Notes: This table presents a set of estimations that test the robustness of the accelerating effect in the context of VC involvement using different sets of dependent variables. The three panels repeat the main estimations as displayed in Table 6. Only here, the dependent variables are the citation weighted patent counts (Panel A) and the patent originality score as defined in Hall *et al.* (2001) (Panel B). In Panel C, estimation specifications are equivalent to those displayed in Column 6 of Table 6 and use different patent stock measures as dependent variable. In Columns 1-3 the dependent variable is the accumulated patent stock measured in past patent filings (in logs) using different discount rates: Column 1 follows Hall *et al.* (2005) and uses a discount rate of 15%; Column 2 uses a discount rate of 0.5/8 which resembles the average lifespan of patents in Europe as 50% of patents are lapsed within the first 8 years (see Harhoff 2016); The specification in Column 3 does not discount the patent stock. In Columns 4-6 we use the accumulated, citation-weighted patent stock and employ the same three variants of the discount rates. Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA10: Robustness tests: Investor involvement and the accelerating effect

Panel A: Testing for survivorship bias

Dep. variable:	*LogPatFilings*					
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Med-post × Invo^{high}	0.207**	0.242***	0.273**	0.212**	0.266***	0.286**
	(0.081)	(0.081)	(0.110)	(0.095)	(0.093)	(0.116)
VC × Med-post	-0.002	-0.087*	-0.057	-0.003	-0.094*	-0.074
	(0.053)	(0.048)	(0.060)	(0.063)	(0.054)	(0.063)
Med-post × Invo^{high}	-0.123*	-0.082*	-0.029	-0.111	-0.076	-0.019
	(0.065)	(0.048)	(0.043)	(0.079)	(0.53)	(0.051)
Invo^{high} definition:	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*
Sample:	survivors until $t > 2$			survivors until $t > 4$		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.47	0.47	0.47	0.49	0.49	0.49
Obs.	3,208	3,208	3,208	2,539	2,539	2,539

Panel B: Testing alternative definitions of investor reputation

Dep. variable:	*LogPatFilings*						*CitsFilings*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VC × Post × Invo^{high}	0.127	0.209**	0.541	0.357*	0.101	0.109	0.172	0.225**
	(0.092)	(0.084)	(0.332)	(0.216)	(0.139)	(0.113)	(0.113)	(0.088)
VC × Post	0.018	-0.059	0.035	-0.008	0.042	-0.009	-0.094*	-0.090*
	(0.043)	(0.041)	(0.038)	(0.037)	(0.040)	(0.039)	(0.040)	(0.053)
Post × Invo^{high}	-0.010	-0.040	-0.058	-0.125	-0.076	-0.056	-0.073	-0.122**
	(0.061)	(0.048)	(0.160)	(0.078)	(0.040)	(0.053)	(0.065)	(0.059)
Invo^{high} definition:	REP_{nbrs}		REP_{world}		REP_{US}		REP_{nbrs}	
Post definition:	Post	Med-post	Post	Med-post	Post	Med-post	Post	Med-post
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.45	0.45	0.46	0.45	0.45	0.45	0.41	0.41
Obs.	4,259	4,259	4,259	4,259	4,259	4,259	3,560	3,560

(*continued on next page*)

Table IA10: Robustness tests (*continued*)

Panel C: The role of syndication in the accelerating effect and VC investor involvement

Dependent variable:	*LogPatFilings*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VC × Med-post	-0.204**	-0.035	0.025	-0.065	-0.112	-0.073	-0.048
	(0.089)	(0.069)	(0.067)	(0.092)	(0.068)	(0.058)	(0.056)
Med-post × Invo^{high}	-0.001	0.001	0.025	0.048	-0.120*	-0.192	
	(0.066)	(0.064)	(0.068)	(0.080)	(0.071)	(0.151)	
VC × Med-post × Invo^{high}	0.383***	0.242**	0.209	0.030	0.195*	0.392	
	(0.111)	(0.111)	(0.133)	(0.114)	(0.117)	(0.249)	
Med-post × *Synd*							-0.056
							(0.047)
VC × Med-post × *Synd*							0.134*
							(0.081)
Invo^{high} definition:	CVC	EXP	REP	CVC	EXP	REP	-
Sample (*Synd*):	Syndicated first deal			No syndication			Any
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.47	0.47	0.47	0.50	0.50	0.50	0.47
Obs.	1,891	1,891	1,891	1,665	1,665	1,665	3,560

Notes: This table presents a set of estimations that test the robustness of the accelerating effect in the context of VC involvement. In Panel A, the estimations test for potential survivorship biases. To this end, regressions in Columns 1-3 and 4-6 are specified equivalent to Columns 2, 4, and 6 in Table 6. Only here, the sample are subsets of firms which survived at least the first three (Columns 1-3) or five (Columns 4-6) years after the initial VC investment. Panel B tests different specifications of the reputation measure using estimation specifications that are equivalent to Columns 3 and 6 in in Table 6. Reputation is measured in the investors' the number (instead of the market value) of successful exists as a share of the total number of exits in Europe, REP_{nbrs} (Columns 1-2) or the reputation measured by exits as a fraction of accumulated exits worldwide (Columns 3-4) or in the US (Columns 5-6), respectively. Columns 7 and 8 repeat the first two specifications but use the citation-weighted patent count as the dependent variable. Panel C is equivalently structured to Panel A but distinguishes firms whose initial VC investment came from multiple investors (Columns 1-3) or single investors (Columns 4-6). Moreover, the regression in Column 7 is similar to the augmented accelerating effect estimations as defined in Equation (12) but uses the indicator *Synd* instead of $Invo^{high}$. *Synd* is equal to one for firms whose initial VC investment came from multiple investors and zero otherwise. Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA11: The accelerating effect: Distinguishing first investment characteristics

Panel A: The size of the first VC deal and the accelerating effect

Dep. variable:	*LogPatFilings*					
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Med-post × $Invo^{high}$	0.138	0.215**	0.236*	0.310*	0.192	0.231
	(0.093)	(0.093)	(0.129)	(0.163)	(0.141)	(0.200)
VC × Med-post	-0.122	-0.115**	-0.068	-0.145	0.025	0.048
	(0.075)	(0.058)	(0.049)	(0.139)	(0.081)	(0.084)
Med-post × $Invo^{high}$	0.013	-0.140**	-0.054	0.016	0.129	0.016
	(0.062)	(0.056)	(0.088)	(0.099)	(0.081)	(0.101)
$Invo^{high}$ definition:	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*
Investment size:	Small deal ($< Q50$)			Large deal ($> Q50$)		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.48	0.48	0.48	0.50	0.50	0.50
Obs.	2,266	2,254	2,266	1,288	1,276	1,288

Panel B: Plausibility test: follow-on investments

Dep. variable:	*LogPatFilings*					
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Med-post × $Invo^{high}$	0.338***	0.239**	0.319**	0.054	0.251**	-0.052
	(0.119)	(0.114)	(0.129)	(0.106)	(0.110)	(0.180)
VC × Med-post	-0.194**	-0.070	-0.041	-0.062	-0.110*	-0.028
	(0.096)	(0.073)	(0.067)	(0.087)	(0.064)	(0.056)
Med-post × $Invo^{high}$	-0.080	-0.060	-0.084	0.160**	-0.091	0.123
	(0.077)	(0.064)	(0.071)	(0.070)	(0.076)	(0.143)
$Invo^{high}$ definition:	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*
Sample:	With follow-on investment			Without follow-on investment		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.50	0.50	0.50	0.48	0.48	0.47
Obs.	1,939	1,939	1,939	1,613	1,589	1,613

Notes: This table presents a set of estimations that test the robustness of the accelerating effect in the context of VC involvement. In Panel A, the estimations test for differences in the accelerating effect according to the size of the first VC deal. Regressions in Columns 1-3 and 4-6 are specified equivalent to Columns 2, 4, and 6 in Table 6. Only here, the sample comprises subsets of firms with below (Columns 1-3) or above (Columns 4-6) median sized first VC investment rounds. Below, includes those firms with missing deal size information. In Panel B, the estimations test for differences in the accelerating effect depending on whether firms obtained follow-on investments, using the same setup as in Panel A. Only here, the sample are subsets of firms with (Columns 1-3) or without (Columns 4-6) at least one follow-on VC investment round. Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA12: Industry-level patenting intensity and VC outcomes

Panel A: Enabling effect

	$Pr(Patent)$			
	(1)	(2)	(3)	(4)
VC	1.216***	1.384***	1.188***	1.295***
	(0.212)	(0.206)	(0.208)	(0.277)
PatIntensity^{lo}	-1.498***			
	(0.308)			
VC × PatIntensity^{lo}	0.044			
	(0.338)			
PatIntensity^{med}		0.815**		1.302***
		(0.325)		(0.362)
VC × PatIntensity^{med}		-0.415		-0.251
		(0.338)		(0.403)
PatIntensity^{hi}			1.370***	1.760***
			(0.320)	(0.338)
VC × PatIntensity^{hi}			0.055	-0.048
			(0.351)	(0.393)
Firm-level controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Chi^2	1178.15	943.73	1229.07	5709.25
Obs.	17,304	17,304	17,304	17,304

(*continued on next page*)

Table IA12: Industry-level patenting intensity and VC outcomes (*continued*)

Panel B: Accelerating effect

Dep. variable:	*LogPatFilings*)			
	(1)	(2)	(3)	(4)
VC × Med-post	0.022	-0.008	0.059	0.024
	(0.050)	(0.048)	(0.049)	(0.058)
PatIntensity^{lo}× Med-post	-0.113***			
	(0.041)			
VC × PatIntensity^{lo} × Med-post	0.003			
	(0.077)			
PatIntensity^{med} × Med-post		-0.043		0.055
		(0.051)		(0.050)
VC × PatIntensity^{med} × Med-post		0.105		0.073
		(0.090)		(0.095)
PatIntensity^{hi}× Med-post			0.119**	0.149***
			(0.049)	(0.049)
VC × PatIntensity^{hi}× Med-post			-0.082	-0.047
			(0.083)	(0.088)
Firm-level controls	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes
Rel. year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
R^2	0.47	0.47	0.47	0.47
Obs.	3,560	3,560	3,560	3,560

Notes: This table provides the estimation results on the enabling and accelerating effects across different industry-level patenting intensities and VC outcomes. Panel A displays a variant of the augmented enabling effect specification, as defined in Equation (11) and displayed in Columns 1-3 of Table 5. Only here, we include an indicator for different levels of sector-level patenting intensities, $PatIntensity$ instead of the Invo^{high}-dummy. In Column 1, 2, and 3, the indicator is equal to one for all firms that operate in low (PatIntensity^{lo}), medium (PatIntensity^{med}), and high (PatIntensity^{hi}) patenting intensive sectors and zero otherwise, respectively. Column 4 contains indicators for both high and medium patenting intensive sectors. Patenting intensity is specified as defined in Table 7. Panel B applies the same logic but estimates respective effects in the context of the accelerating effect as defined in Equation (12). Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA13: Robustness tests: Treatment heterogeneity regarding firms' patenting experience

Panel A: Firms' ex-ante patenting experience and differential effects on citation-weighted patent outcomes

Dep. variable:	*CitsFilings*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VC × Med-post × $Invo^{high}$	0.228^{*}	0.160	0.440^{***}	0.096	0.299^{**}	0.374	0.082	0.068	0.340
	(0.134)	(0.118)	(0.153)	(0.135)	(0.137)	(0.244)	(0.188)	(0.174)	(0.216)
Med-post × $Invo^{high}$	-0.000	-0.025	-0.092	-0.105	-0.240^{**}	-0.224	-0.037	-0.076	-0.032
	(0.111)	(0.089)	(0.122)	(0.103)	(0.098)	(0.175)	(0.148)	(0.125)	(0.135)
VC × Med-post	-0.101	-0.000	-0.023	-0.015	-0.064	-0.005	-0.167	-0.135	-0.173^{*}
	(0.112)	(0.074)	(0.060)	(0.100)	(0.081)	(0.069)	(0.155)	(0.115)	(0.094)
$Invo^{high}$ definition:	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*
Pre-VC patent stock size:	Small			Medium			Large		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.48	0.48	0.49	0.46	0.46	0.46	0.45	0.45	0.45
Obs.	1,178	1,176	1,178	1,094	1,082	1,094	1,164	1,154	1,164

Panel B: Sector-level patenting intensity and differential effects on citation-weighted patent outcomes

Dep. variable:	*CitsFilings*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VC × Med-post × $Invo^{high}$	-0.075	-0.144	0.339	0.131	0.042	0.366	0.237^{*}	0.321^{**}	0.421^{**}
	(0.171)	(0.196)	(0.225)	(0.143)	(0.151)	(0.248)	(0.142)	(0.130)	(0.201)
Med-post × $Invo^{high}$	0.017	0.112	-0.209	-0.086	-0.011	0.031	-0.094	-0.234^{**}	-0.109
	(0.116)	(0.133)	(0.135)	(0.097)	(0.108)	(0.202)	(0.114)	(0.092)	(0.172)
VC × Med-post	0.107	0.128	-0.033	0.040	0.107	0.095	-0.276^{**}	-0.221^{**}	-0.180^{**}
	(0.116)	(0.106)	(0.098)	(0.096)	(0.092)	(0.069)	(0.122)	(0.085)	(0.072)
$Invo^{high}$ definition:	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*
Sector-level patenting intensity:	Low			Medium			High		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.51	0.51	0.51	0.48	0.49	0.48	0.41	0.42	0.42
Obs.	903	903	903	1,000	988	1,000	1,620	1,608	1,620

Notes: This table provides robustness tests on Table 7. The regressions are specified equivalently, only here the dependent variable is the citation-weighted measure of patent filings (*CitsFilings*). Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table IA14: The enabling effect and industry-level patenting intensity

	$Pr(Patent)$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VC	1.356***	1.394***	1.155***	1.192**	0.985**	0.764**	1.233***	1.704***	1.294***
	(0.499)	(0.397)	(0.317)	(0.465)	(0.403)	(0.329)	(0.554)	(0.471)	(0.314)
Invo^{high}	0.191	0.270	0.130	-0.358	-0.082	-1.208	-0.628	0.618	-0.960
	(0.541)	(0.490)	(0.635)	(0.555)	(0.564)	(1.082)	(0.601)	(0.574)	(1.042)
VC × Invo^{high}	-0.286	-0.507	0.060	-0.381	-0.008	1.663	0.299	-0.391	1.328
	(0.585)	(0.537)	(0.686)	(0.607)	(0.629)	(1.155)	(0.639)	(0.591)	(1.051)
Invo^{high} definition:	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*	*CVC*	*EXP*	*REP*
Sector-level patenting intensity:	Low			Medium			High		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chi^2	691.88	681.46	685.22	3441.67	85,814.88	2859.90	6760.90	6696.89	7181.55
Obs.	12,508	12,508	12,508	2,802	2,802	2,802	1,994	1,994	1,994

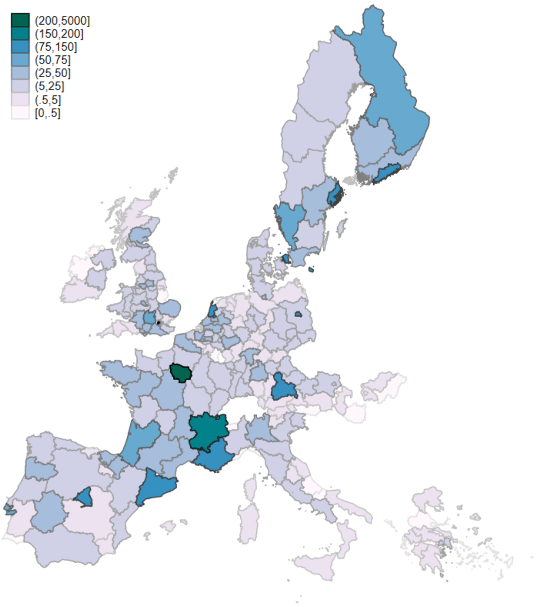
Notes: This table displays differential effects of VC involvement in the context of sector-level ex-ante patenting intensities, similar to Panel B of Table 7. Only here, we use the sample of pre-VC non-patenting firms (V^0 and N^0) and estimate the augmented enabling effect specification, as defined in Equation (11) and displayed in Columns 1-3 of Table 5. Standard errors are clustered at the firm level. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Internet Appendix B : Figures

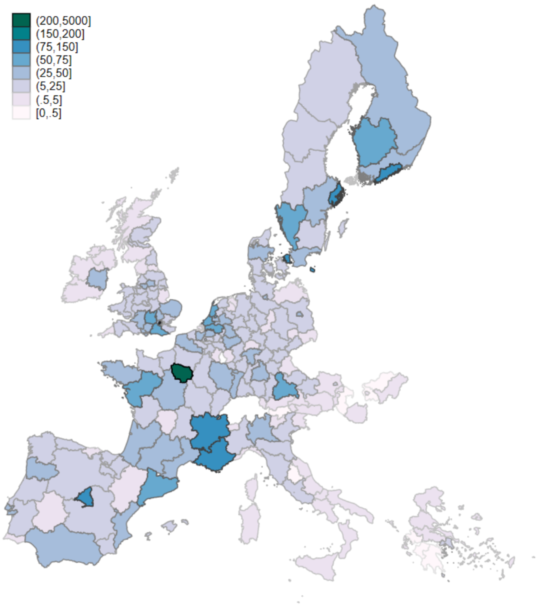
Figure IA1: Geographical distribution and of treated startups in the matched sample

Panel A: Geographical distribution of treated and comparison group firms

VC-backed startups (V)



Comparison group (N)



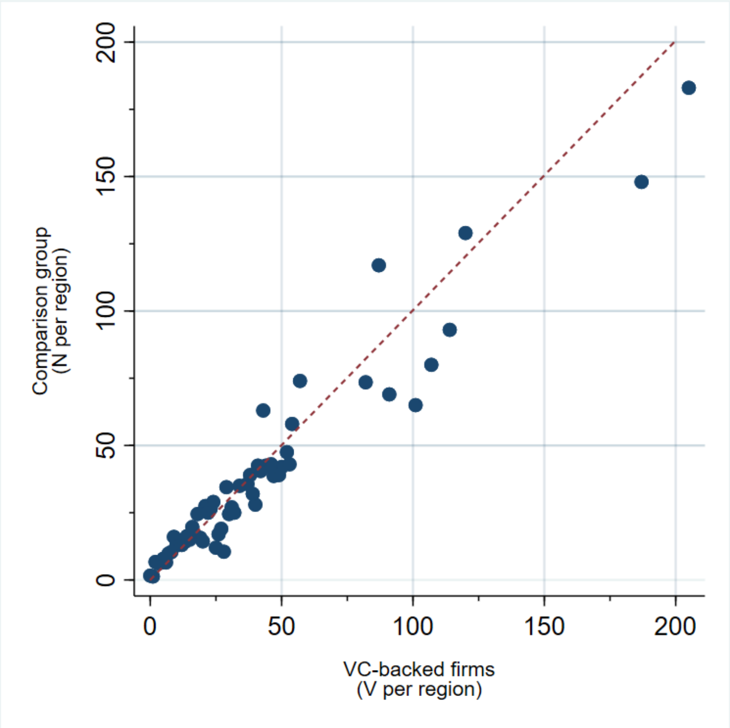
NUTS-2 region with highest share of sample startups, by country

Country	NUTS-2 region (code)	Capital region	Share of domestic startups in region	Share of three largest regions
Ireland	Eastern and Midland (IE06)	yes	82.8%	100%
Greece	Attiki (EL30)	yes	61.1%	80.6%
Denmark	Hovedstaden (DK01)	yes	59.5%	84.5%
Finland	Helsinki-Uusimaa (FI1B)	yes	47.9%	85.6%
Portugal	Área Metropolitana de Lisboa (PT17)	yes	43.9%	93.0%
Austria	Wien (AT13)	yes	41.7%	72.9%
Hungary	Budapest (EL30)	yes	40.0%	70.0%
France	Ile-de-France (FR10)	yes	39.9%	60.2%
Sweden	Stockholm (SE11)	yes	38.4%	70.4%
Italy	Lombardia (ITC4)	no	28.7%	50.4%
Spain	Comunidad de Madrid (ES30)	yes	27.4%	57.1%
Netherlands	Noord-Holland (NL32)	yes	23.0%	54.4%
Great Britain	Inner London - West (UKI3)	yes	21.1%	33.2%
Belgium	Brussels Hoofdstedelijk Gewest (BE10)	yes	18.3%	49.5%
Germany	Oberbayern (DE21)	no	13.0%	32.6%

(*continued on next page*)

Figure IA1: Geographical distribution of treated startups in the matched sample (*continued*)

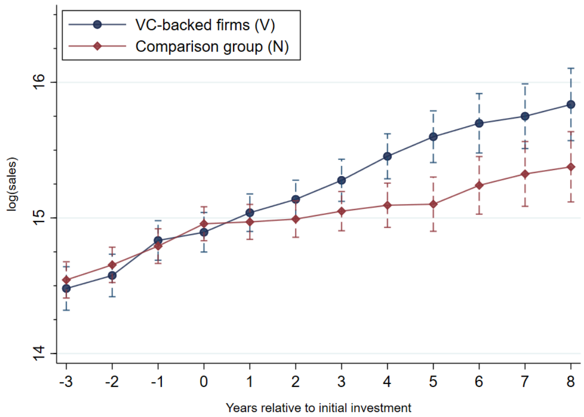
Panel B: Binned scatterplot comparing location frequencies of treated and control group firms



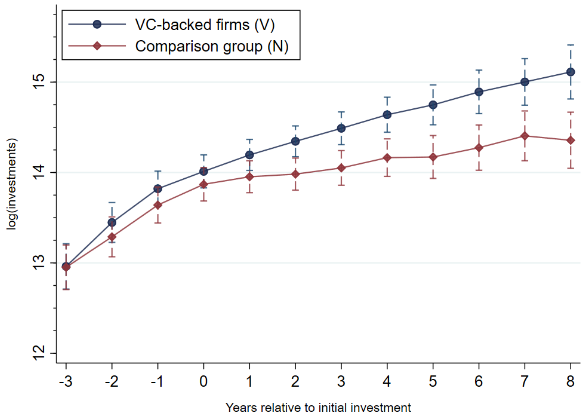
Notes: In Panel A, the heatmaps display the distribution of startups from the treated (V^1 and V^0 in the left graph) and comparison group (N^1 and N^0 , in the right graph) on the NUTS-2 region level. The table below the figure shows the corresponding region in each sample country that locates the highest share of domestic startups. For example, 39.9% of French startups are located in the Ile-de-France region (NUTS-2 region FR10). The table further displays whether the respective region is home of the countries capital. The last column displays the cumulative share of the three largest regions in respective countries. Note that differences in these shares not only reflect differences in geographical concentration of startups to specific regions but also to country-specific differences in the definition of NUTS-2 regions. For example, France had 66.7 million inhabitants in 2016 and 27 corresponding NUTS level 2 regions, while Great Britain had 52% more NUTS-2 regions (41) with a similar population size of 65.6 million in 2016. Panel B plots the frequency of startups being located in specific NUTS-2 regions, comparing the frequencies of treated (x-axis) and control group firms (y-axis). The dashed 45-degree line provides a reference for even distributions of respective groups. The bin sizes of the scatterplot are set to 40.

Figure IA2: Firm development of VC-backed firms and the comparison group

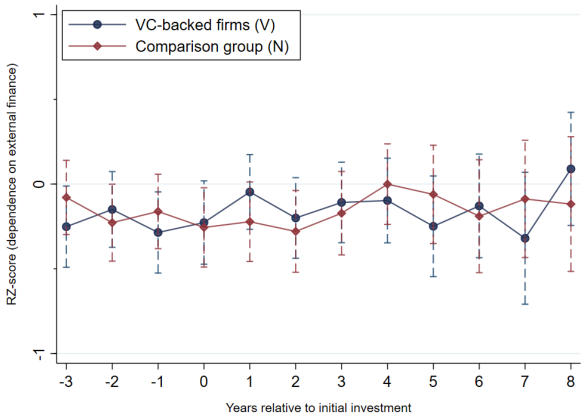
Panel A: $logSales$



Panel B: $logInvestments$



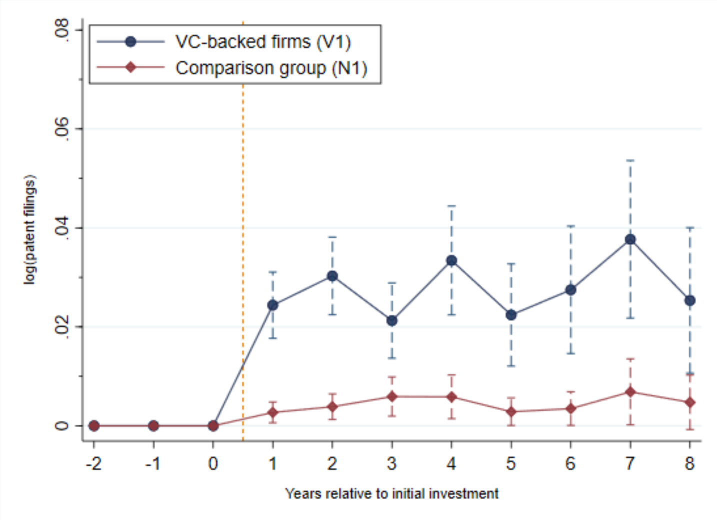
Panel C: $RZscore$



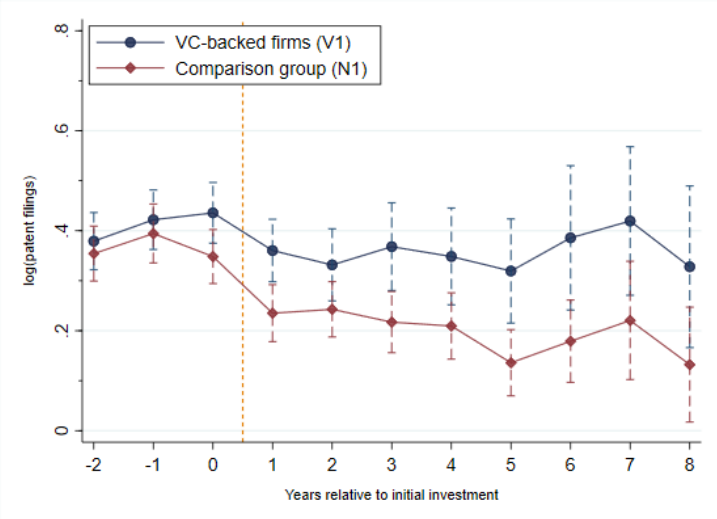
Notes: This graph plots different firm-level measures for the treated and control group over the years relative to the initial VC investment into firms of the treated cohort. Here, the treatment group refers to any firm that has received VC funding, while their non-funded counterparts comprise the control group. Panel A displays firms' average total sales (in logs). Panel B displays total investments, including capital and operating expenses (in logs). Panel C displays the RZ score which reflects firms demand of external financing. We follow Rajan and Zingales (1998) and calculate the RZ score as the fraction of investments (capex) not covered by internal funds (cashflow); $RZscore_{it} = (capex_{it} - cashflow_{it})/capex_{it}$. To avoid outliers affecting the results, we winsorize the score of each firm at the five percent level. The whiskers span the 95 percent confidence interval.

Figure IA3: Robustness test on patenting patterns

Panel A: Pre-VC non-patenting firms



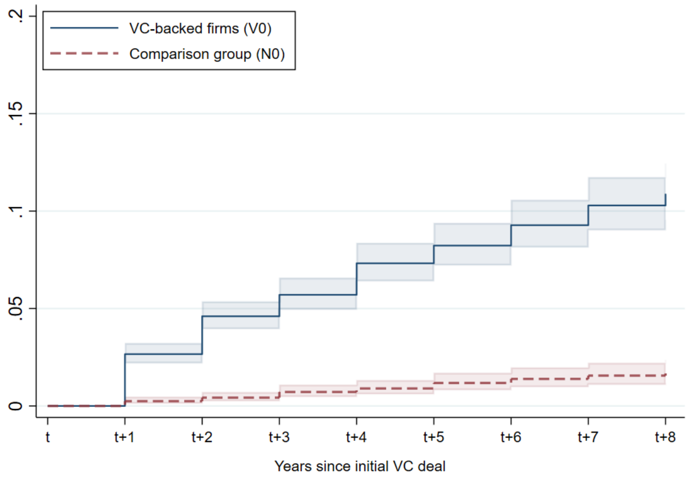
Panel B: Pre-VC patenting firms



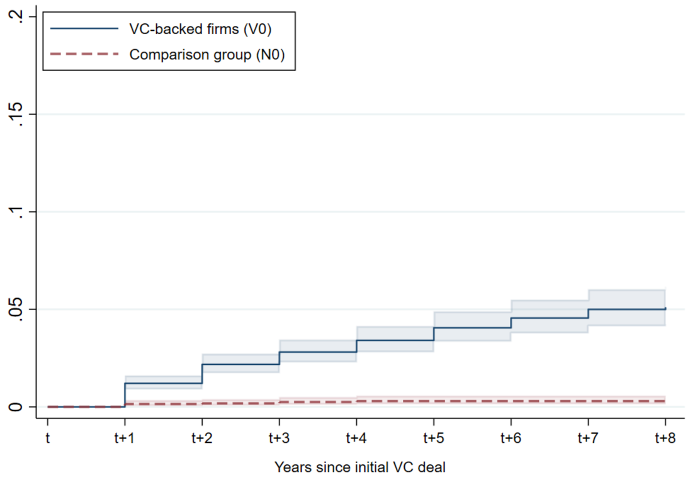
Notes: This figure displays robustness tests on the descriptive statistics displayed in Figure 2. The graphs in Panel A and B are equivalent to those in Panel B and C of Figure 2, only here, we exclude firms with only one or two observations in the pre-treatment period. The whiskers span the 95 percent confidence interval.

Figure IA4: Non-Patenters: Cumulative hazard estimates for high-quality patents

Panel A: Patents with at least one citation



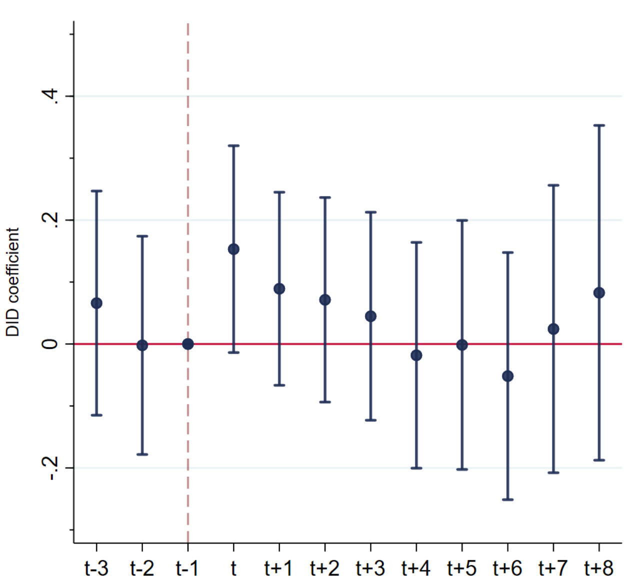
Panel B: Patents with top quartile citations



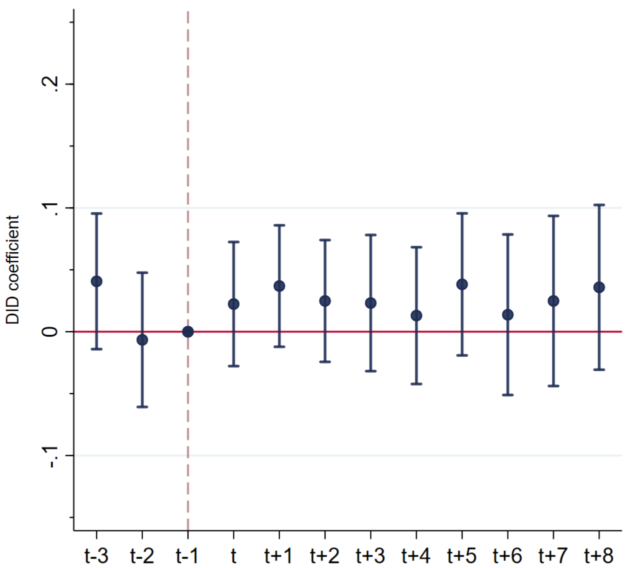
Notes: This graph displays the Nelson-Aalen cumulative hazard estimates for the treatment versus control group. The treatment group comprises firms that have received VC funding but did not file patents before the initial round of funding, while their non-funded counterparts comprise the control group. Firms drop out of the dataset right after they filed their first patent. In Panel A, the estimations only include patents that have received at least one citation in the five years following the application and can thus be referred to as patents with an effect. In Panel B, the estimations only include particularly influential patents, i.e., within the top quartile of the citation distribution. The shaded areas represent the 95 percent confidence intervals.

Figure IA5: Accelerating effect on patent quality: Event study regressions

Panel A: *CitsFilings*



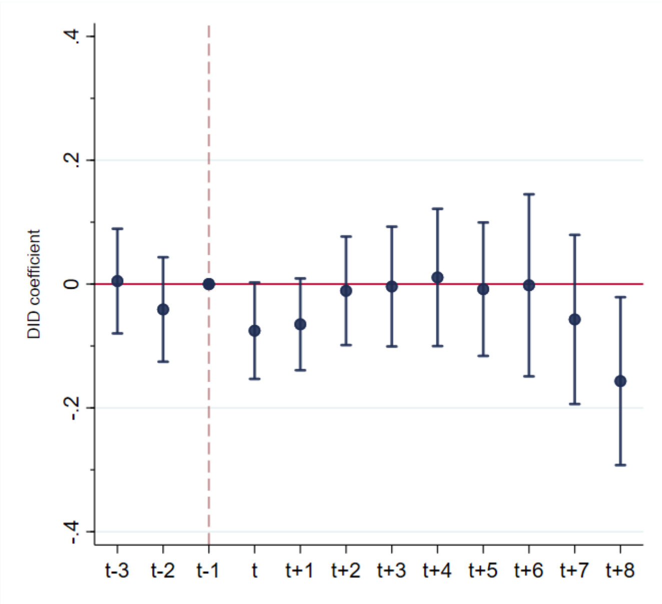
Panel B: *OriginalityAvg*



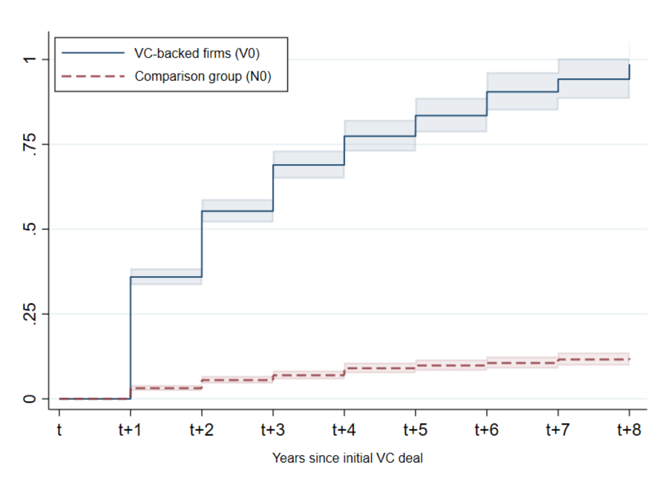
Notes: The figure shows the plot of coefficients for the event study type regression from Equation (10). The dependent variable in Panel A is the logarithm of citation weighted filings and in Panel B the average originality index score as defined in Table IA1 (Appendix). Both panels display the DID coefficients that interact year dummies with the VC indicator. Years are denoted as the strata-specific relative years to the initial VC investment. Whiskers span the 95 percent confidence intervals.

Figure IA6: The baseline effects using an alternative matching approach

Panel A: Accerlerating effects



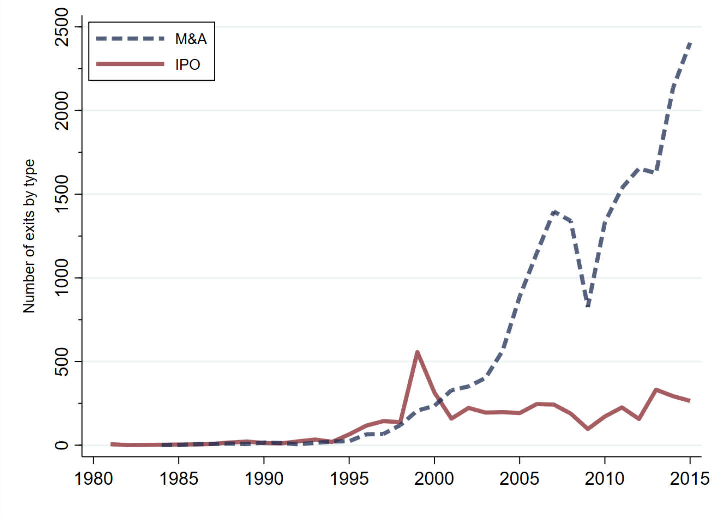
Panel B: Enabling effects



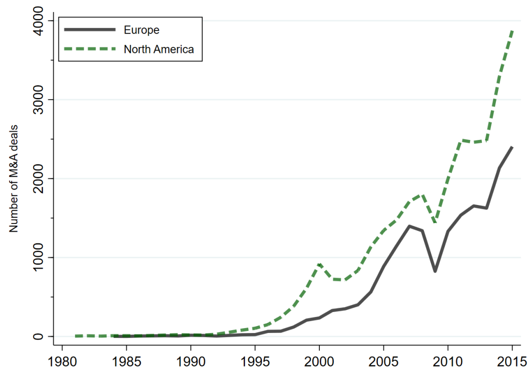
Notes: These figures plot the baseline effects using an alternative matching approach. Panel A and B repeat the main analysis of the accererating and enabling effects equivalent to Figures 4 and 3, respectively. Only here the sample is constructed using the average matching partner within strata, instead of the closest neighbors. Specifically, we repeat the matching exercise and take the average expression of all firm-level, time-variant observables, including the control variables and the dependent variable. All other relevant time-invariant variables (founding year, industry affiliation, and country) are equal for treated and control group firms due to the matching process. Using this sample, we re-estimate the two main effects by repeating the estimations from Equation (10) and the underlying Nelson-Aalen cumulative hazard estimation from Figure 3, accordingly. Years are denoted as the strata-specific relative years to the initial VC investment. In Panel A, whiskers span the 95 percent confidence intervals. Similarly, in Panel B, the shaded areas around the hazard estimates reflect the 95 percent confidence intervals.

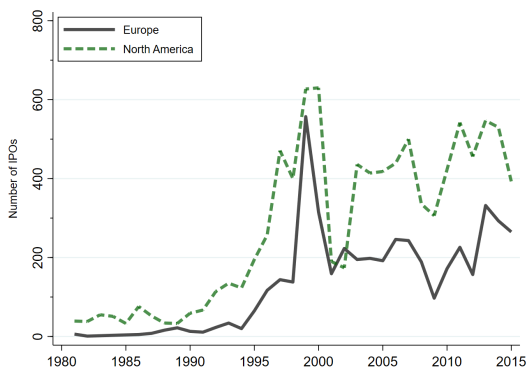
Figure IA7: Exit strategies of startups using Crunchbase data (1980-2015)

Panel A: Exits in Europe by types - M&A versus IPO



Panel B: Total number of exits by type and region

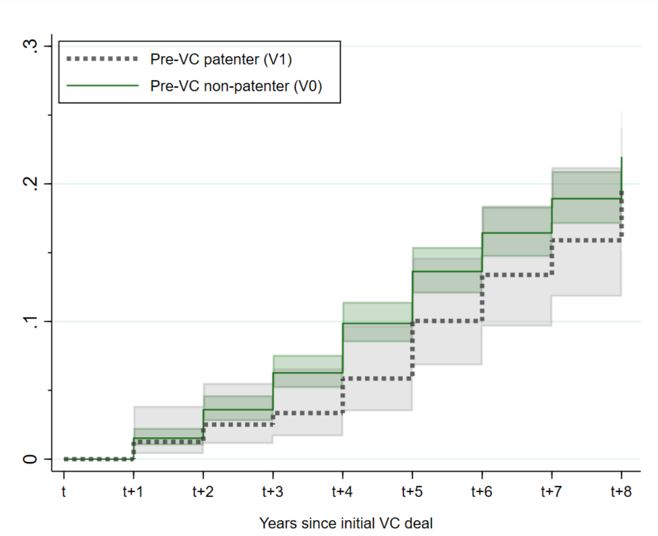




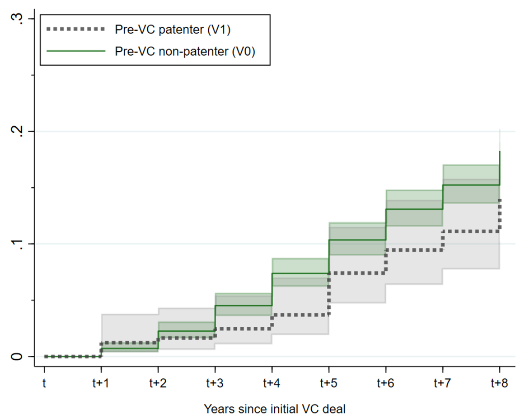
Notes: This graph displays aggregate statistics on the total number of successful exits in Europe and the US from 1980 until 2015. The data source is Crunchbase (July 2023 vintage). Panel A plots the total number of M&A deals and IPOs of startups that are headquartered in Europe. Panel B displays the total number of M&A deals of startups located in Europe and the US (left graph) and the total number of IPOs in respective countries (right graph).

Figure IA8: Time to exit for pre-VC patenting versus non-patenting firms (V^1 *versus* V^0)

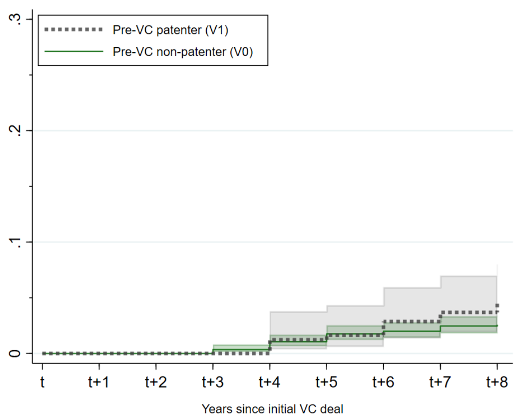
Panel A: Any successful exit



Panel B: Acquisitions



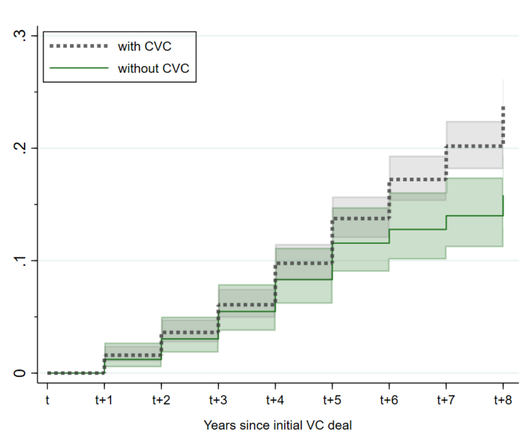
Panel C: IPOs



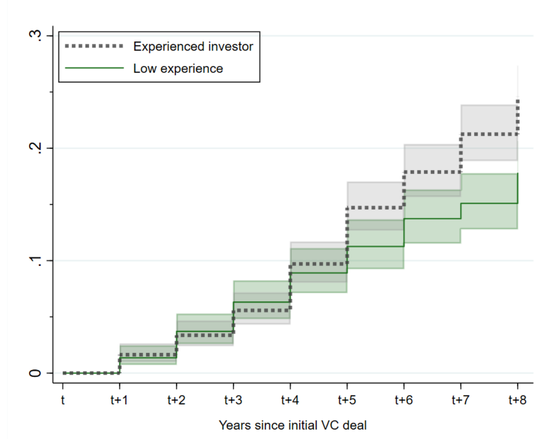
Notes: This graph illustrates the timing of VC-backed firms achieving certain performance targets, i.e., a successful exit via an acquisition (Panel A), IPO (Panel B), or both (Panel C). It displays the Kaplan-Meier failure estimates (hazard rates) of the timing of respective milestones on the firm-year level. The hazard rate is unconditional on having an exit and is estimated for firms with and without any pre-VC patents (i.e., V^1 and V^0). The data starts in the year in which respective firms receive their initial VC funding.The shaded areas around the hazard rates mark the 95% confidence intervals.

Figure IA9: Time to exit across different VC-backed startup subgroups (V^1 *and* V^0)

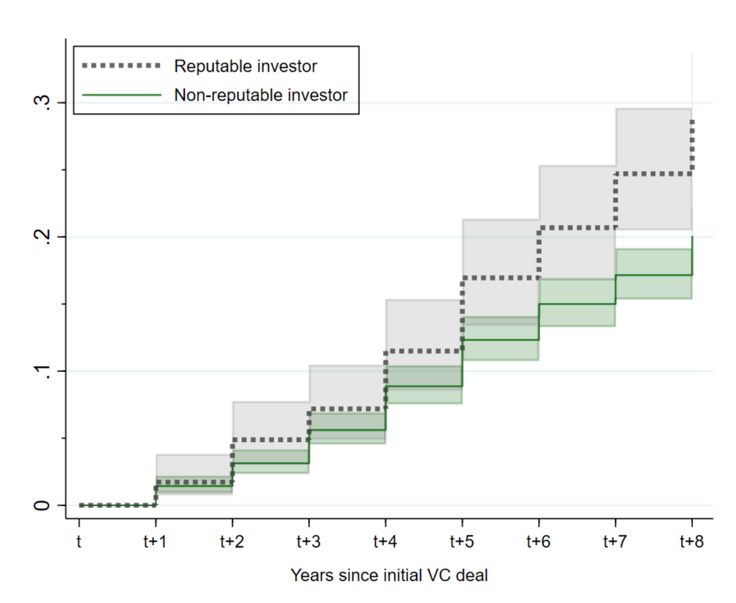
Panel A: Corporate VC



Panel B: Investor experience



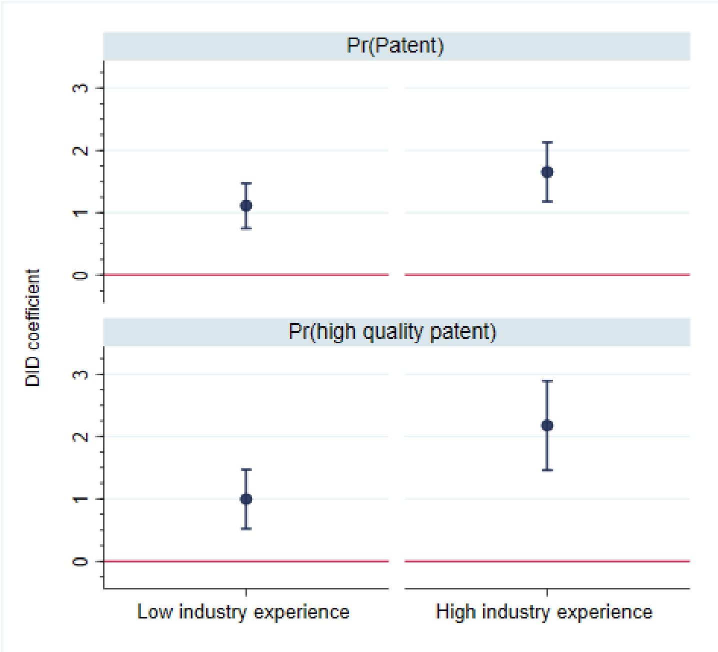
Panel C: Investor reputation



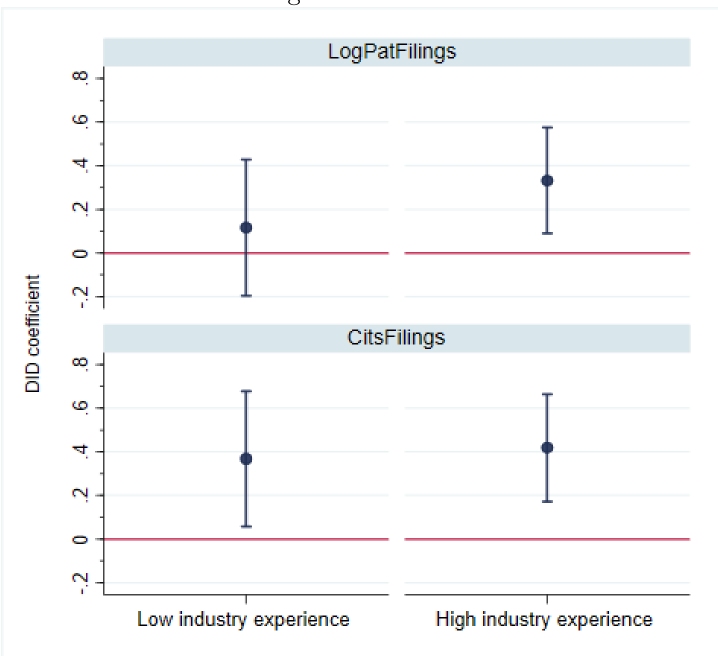
Notes: This graph illustrates the timing of VC-backed firms achieving certain performance targets, similar to Panel C of Figure IA7. It displays the Kaplan-Meier failure estimates (hazard rates) of the timing of acquisitions or IPOs on the firm-year level and distinguishes VC-backed firms by the degree of involvement of their investors. Panel A distinguishes Corporate VCs and others (CVC). Panel B distinguishes more or less experienced independent VCs (EXP). Panel C distinguishes more or less reputable independent VCs (REP). The hazard rate is unconditional on having an exit. The data starts in the year in which respective firms receive their initial VC funding.The shaded areas around the hazard rates mark the 95 percent confidence intervals.

Figure IA10: Treatment heterogeneity depending on investors' sector-specific experience

Panel A: Enabling effect differences across investors



Panel B: Accelerating effect differences across investors



Notes: This graph plots the DID estimation coefficients on regressions that estimate the accelerating ($VC \times$ Med-post $\times$ $Invo^{high}$) and enabling effect ($VC \times Invo^{high}$), as defined in Equations (12) and (11). Here, investor involvement is measured using the indicator for reputable VCs (REP). The coefficients are estimated for split samples that distinguish whether the VC investor of a firm has "patenting experience", i.e., has previously invested in a firm that is active in a patenting-intensive industry, or not, which is labeled as high versus low industry experience. Panel A uses patent filings as the dependent variable, while Panel B displays DID coefficients for estimates on quality-weighted patenting outcomes. The upper row in each panel displays estimates on the accelerating effects and the lower row estimates on the enabling effects. The whiskers span the 95 percent confidence intervals