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Enabling or accelerating? The timing of innovation and the different roles of venture capitalists

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ABSTRACT

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 only obtain financial support, while others additionally seek 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.

1. Introduction

Nascent technology-based firms are particularly dynamic regarding their disruptive potential, knowledge spillovers, and innovative capabilities (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

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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, emphasizing that VC investors' roles in fostering startups includes but is not limited to providing financing. Instead, many investors engage as active mentors, refining their target firms' business model and develop effective growth strategies based on their industry-specific knowledge.[1] To detail on this aspect, we show that investor involvement is most beneficial for target firms in cases in which firms benefit most from VCs' industry expertise, with an inverted U-shape relation: 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 offer an explanation for the observed variation between enabling and accelerating effects: Pre-VC patenting firms already have technological expertise that they could convert into inventive output. However, an accelerating effect occurs only if the VC introduces additional know-how. Thus, VCs lift general constraints to enable patenting for startups without prior patent output. The findings highlight the importance of distinguishing between different VC investors and the timing of the treatment effects to effectively evaluate the role of VCs as specialized investors. In doing so, our analyses provide novel insights into VCs' capabilities to enhance and accelerate patenting even for targets with an established patent record.

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 9614 individual European firms comprising 4807 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,

[1] This argument corroborates prior literature (e.g., Casamatta and Haritchabalet, 2007; Nahata, 2008) and anecdotal evidence that illustrates VCs' active involvement. For instance, the VC *Sequoia Capital*, headed by Alfred Lin, has been a main investor in the online vacation rental platform Airbnb. Lin has an extensive track record of backing successful startups and a proven expertise in the e-commerce industry. Brian Chesky, Airbnb's CEO and co-founder, reports about his relationship with the Sequoia and Alfred Lin: "*I went to art school and had no operations experience. [Alfred] had operational discipline [and is] highly analytical. We are a bit of yin and yang, a symbiotic relationship*" (Forbes, 2021). Until its IPO in 2020, Airbnb filed numerous patents, especially a few years following Sequoia's initial investment in 2009 (see Figures IA1 Appendix).

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 (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.[2] 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 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 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.[3] 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. Eq. (1) can then be re-written as:

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

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 Fig. 1.

Rearranging Eq. (2) further shows that the specific differences in pre-VC patenting activity require two separate analyses using two

[2] 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.

[3] 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.

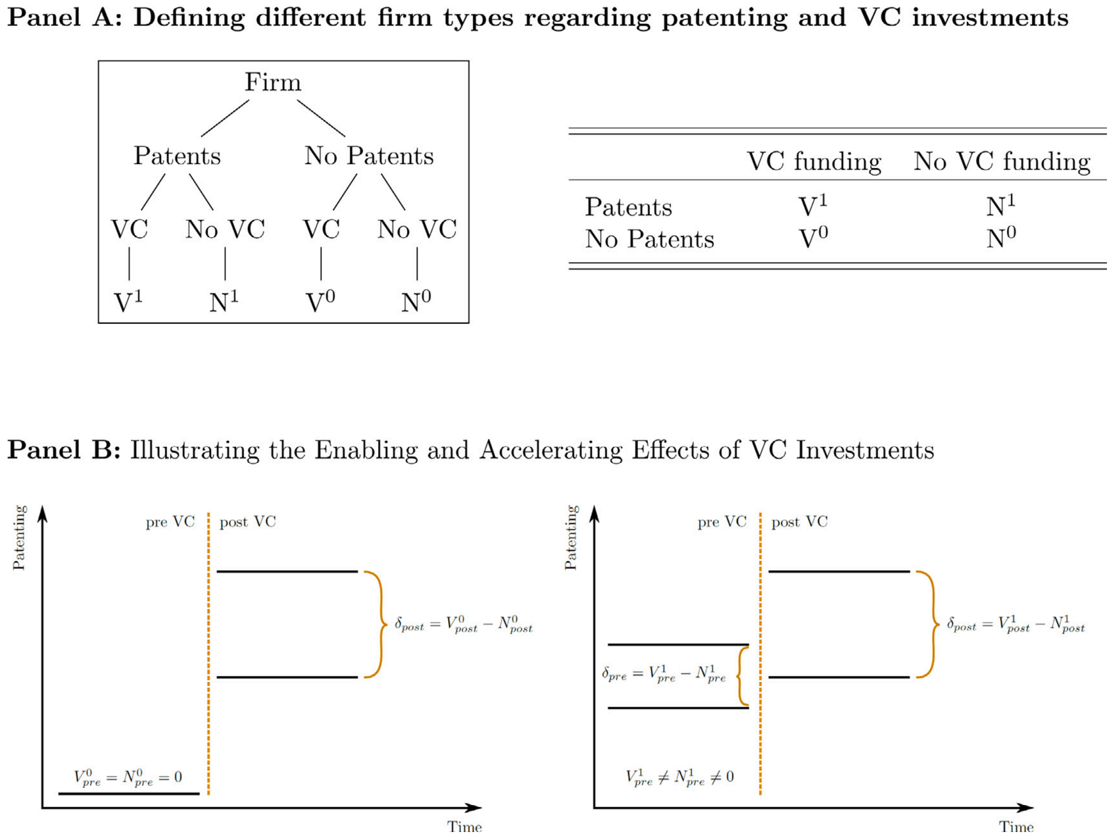


Fig. 1. Graphical illustrations of the conceptual framework. ***Notes:*** These Panels illustrate conceptually the methodological framework of our empirical strategy. Panel A illustrates graphically how we distinguish the different firm types relevant to our conceptual framework, as outlined in Section 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.

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 Fig. 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:

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

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

The timing of the effects: Eqs. (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.[4] We augment this information with detailed data on patents and investors. The patent data comes from PATSTAT, which

[4] 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

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.

Matching approach: The conceptual framework emphasizes the importance of keeping the covariates between VC-backed and comparison group firms fixed (i.e., X' in Eq. (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, as defined in Eq. (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.

Notably, the matching approach also addresses concerns about VC-funded and non-VC-funded firms being on (ex-ante unobservable) different trajectories.[5] 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 IA2 and IA3 (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 (see Rajan and Zingales, 1998) 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 and that they have a similar funding demand as control group firms.

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-year observations, comprising 9602 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.[6]

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.

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

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 (Lerner and Seru, 2022).

[5] 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.

[6] 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).

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	2172
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 %		Obs.	in %
France	2582	26.89	Information & communication	2533	26.38
Great Britain	1840	19.16	Manufacturing	1958	20.39
Germany	1230	12.81	Scientific & technical activities	1876	19.54
Spain	746	7.77	Wholesale/retail trade	1100	11.46
Netherlands	636	6.62	Finance & insurance	620	6.46
Sweden	588	6.12	Admin. & service activities	522	5.44
Other EU countries	1980	20.62	Other Industries	993	10.34
Total	9602	100.00	Total	9602	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.

initial VC investment, which is by definition the same for VC-funded and non-funded firms.

Fig. 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 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 IA4 (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.

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 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 Eq. (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 Eq. (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 Eq. (5) yields very similar results (Column 2). This baseline effect is economically significant; The coefficient (1.360) implies that the instantaneous

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	≥$Q75$	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	1894.06	825.12	1478.67	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 Eq. (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.

probability of filing a patent is about 3.36 times higher for a VC-funded firm than for the comparison group.

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). 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).[7] Formally, the following DID regression estimates the accelerating effect for the matched sample of pre-VC patenting firms:

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

where all indexes are equivalent to Eq. (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 β and captures the average additional

[7] These specifications are advantageous because they mitigate potential issues arising from staggered treatments in two-way fixed effects DID panel estimations as described in Roth et al. (2023). First, the sample comprises a large number of never-treated units and the initial treatment periods are very close in time. Second, consistent with, e.g., Sun and Abraham (2021), we conduct multiple event-study analyses using stacked panels throughout the entire analyses, mitigating concerns about violations of the parallel trends assumption. Third, the extensive matching described in Section 2.3 controls for observable differences across firms, whereas all estimations additionally control for time-variant observables. Fourth, the findings apply using different estimation techniques that control for endogenous sorting into treated and control groups (see Section 4). For these reasons, our estimations are unlikely to suffer from the biases discussed in recent literature.

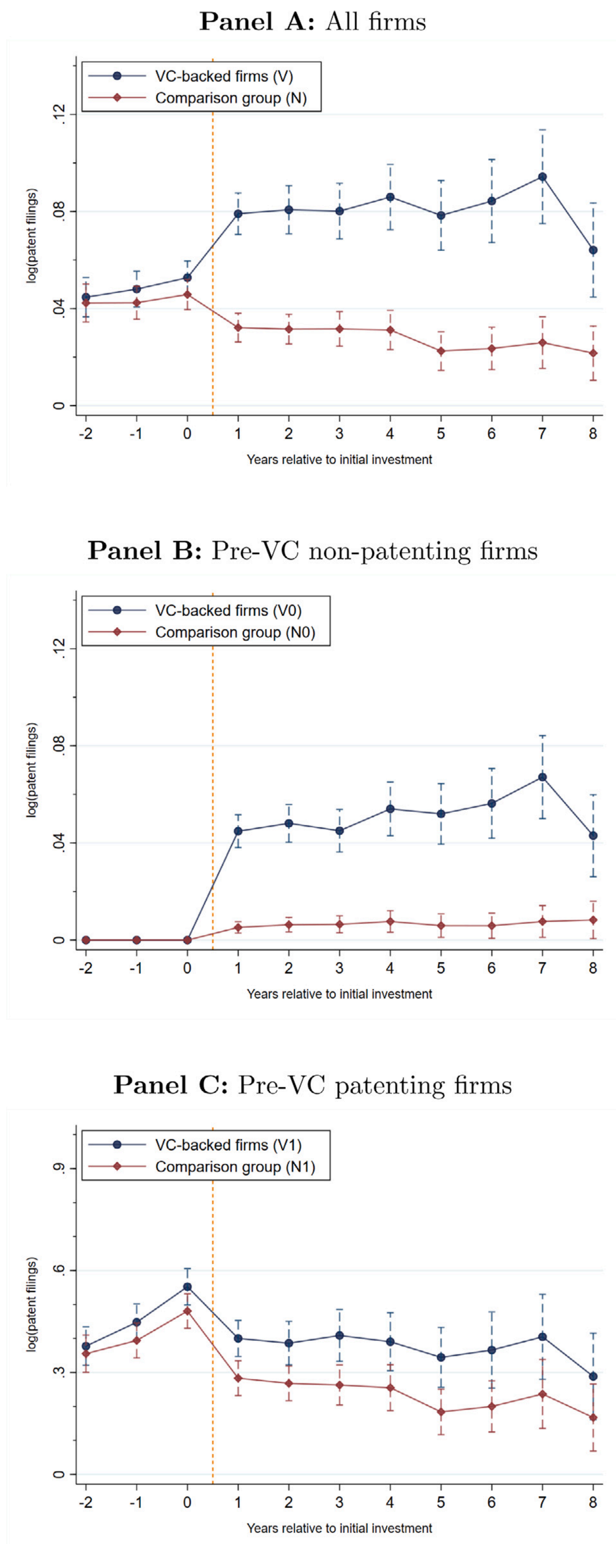


Fig. 2. Mean plots: Average patent filings relative to the VC investment date. ***Notes:*** Panel A shows a comparison of the average VC-funded firms (V) and their non-VC-funded partners (N), irrespective of their pre-VC patent activities. Panels B and C show the potential enabling and accelerating effects 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.

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 Eq. (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.

For consistency, we test this relationship in two 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 ($Med\text{-}Post$). 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).[8] In sum, these 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 Eqs. (5) and (6): $FirmSize$, $Profitability$, $CashFlow$, $DebtRatio$, $FirmAge$, and $Tangibiliy$. Eq. (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:

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

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

[8] All estimates on the control variables have the expected signs, lending support for our model specifications. 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).

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.	4259	4259	4259	4259	4529

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 Eq. (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.

where Eqs. (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 Eqs. (8) and (9) using OLS (see Heckman, 1979; Maddala, 1986).

Estimating Eq. (8) yields the predicted number of patent filings for VC-funded firms had they not received funding, whereas Eq. (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).[9] The estimates for the 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.

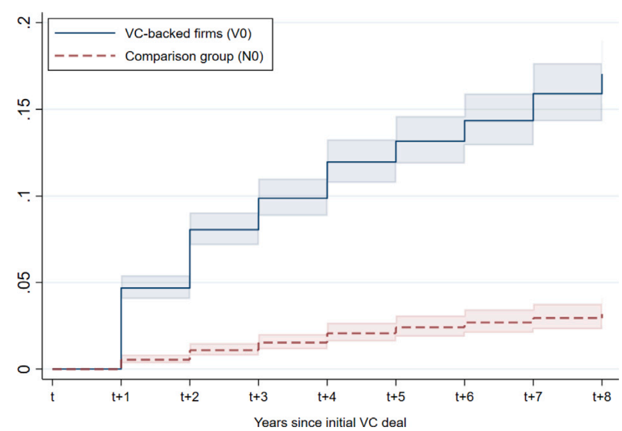


Fig. 3. Enabling effect: The probability (cumulative hazard) of patenting for pre-VC non-patenting firms. ***Notes:*** This graph displays the Nelson-Aalen cumulative hazard estimates for the treatment versus the control group, estimating. The treatment group comprises firms that have received VC funding 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.

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. Fig. 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 IA5, Appendix).

In sum, the above-described results provide consistent and robust evidence of a persistent effect of VC involvement on target firms'

[9] 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.

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.

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 Eq. (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:

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

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 condition (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 Eq. (6).

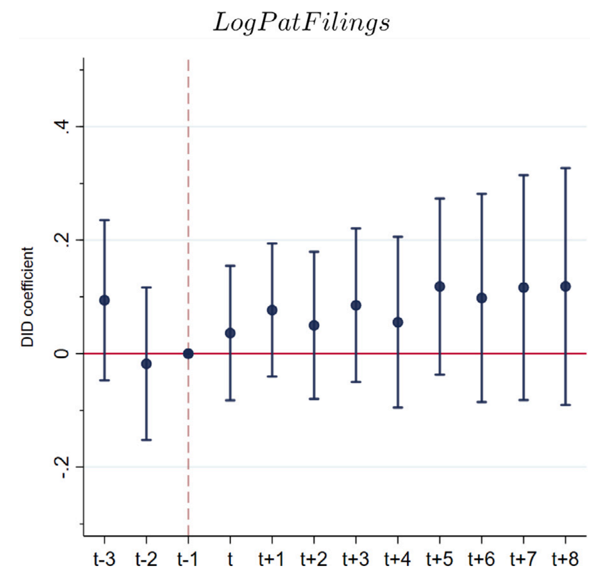


Fig. 4. Accelerating effect of VC investment: Event study regressions. ***Notes:*** The figure shows the plot of coefficients for the event study type regression from Eq. (10). The dependent variable in Panel A is the logarithm of patent filings as defined in Table IA1 (Appendix). The coefficient plots 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.

Results: Fig. 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 IA6 and IA7, 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.

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). More specifically, such active involvement includes the joint development of business plans and commercialization strategies based on VC industry-specific expertise as well as other non-monetary assistance in the form of granting access to existing networks. These dimensions are integral for the work of VCs: As shown in Bernstein et al. (2016), VC investors spend a considerable share of their working time (i.e., about 50%) for monitoring and assisting their portfolio firms. Such involvement is crucial, particularly in the context of highly complex tasks that require both technological know-how and business development, such as patenting activities (Bottazzi et al., 2008; Bernstein et al., 2016).[10] Since direct investor involvement is hard to quantify in observational data, 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 (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 dimensions to measure investor involvement is that active investor involvement requires monetary and non-monetary effort (Casamatta and Haritchabalet, 2007). Research shows that prior *experience* lowers these involvement costs, especially in specialized contexts such as patenting (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 high 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).[11]

We validate the relevance of these three investor characteristics using survival analyses. Figures IA9 and IA10 (Appendix) plot the unconditional probability (Kaplan–Meier failure estimates) of a successful exit by a VC-backed startup over time. First, Figure IA9 shows that there is no statistically significant difference in the probability of pre-VC patenting (V^1) and non-patenting (V^0) startups to successfully 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 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, Figure IA10 shows 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 Eq. (5):

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

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 Eq. (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, controlling for survivorship or the number of investors, using a firm-investor panel that allows to control for investor fixed effects, and for different syndication structures (Table IA7, Appendix). As before, the results are not sensitive to the first funding round size but they are larger for startups with follow-on VC investments (Table IA8, Appendix).

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.

[10] Firms' patenting activities will likely be affected from investor involvement on an extensive and intensive margin. Higher involvement in the form of long-term commitment (extensive margin) is beneficial as developing and realizing new innovative ideas requires time. Better industry- and technology-specific know-how (intensive margin) benefits patenting, which requires expert knowledge along these dimensions.

[11] Figure IA8 (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.

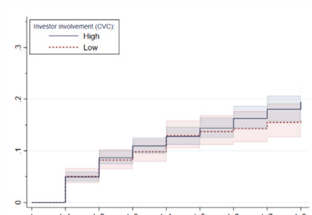
Table 5
VC involvement and the enabling effect.

Panel A: Cox estimations

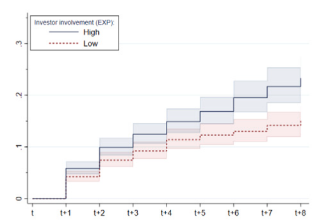
	$Pr(Patent)$					
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Invo^{high}	−0.016	−0.229	0.858			
	(0.350)	(0.327)	(0.505)			
VC	1.320***	1.434***	1.198***			
	(0.293)	(0.239)	(0.184)			
Invo^{high}	−0.189	0.305	−0.461	−0.219	0.063	0.433**
	(0.328)	(0.307)	(0.483)	(0.150)	(0.135)	(0.152)
Invo^{high} definition:	CVC	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	1113.04	1141.12	1142.89	898.20	916.71	921.24
Obs.	17,304	17,304	17,304	8880	8880	8880

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

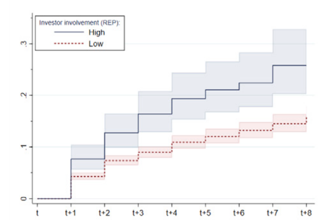
Invo^{high}: CVC



Invo^{high}: EXP



Invo^{high}: REP



Notes: Panel A shows the results of our extended semiparametric survival approach as defined in Eq. (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.

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 Eq. (6) by adding a triple interaction term of the DID estimator ($VC \times Post$) with the indicator for highly involved VCs (Invo_m^{high}):

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

where all variables are defined 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 Eq. (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 $Med\text{-}post$. 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 $Med\text{-}post$ 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.[12]

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 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

[12] A series of robustness tests confirm these findings. First, the results are not sensitive to using different measures of patent quality or firms' patent stock (as defined in Hall et al., 2001, 2005; Harhoff, 2016) as the dependent variable (Table IA9). Second, the results are robust to controlling for survivorship (Panel A of Table IA10). Third, the results are consistent when using alternative definitions of investor reputation, with smaller results when measuring VC reputation outside of Europe (Panel B of Table IA10), and when using a firm-investor-year level panel, including estimations that use investor and investor-year fixed effects (Panel C). On average, there is a moderately positive accelerating effect on startups with syndicated first deals (Panel D).

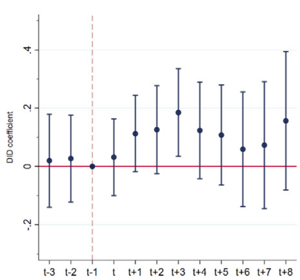
Table 6
VC involvement and the accelerating Effect.

Panel A: Investor involvement and the accelerating effect

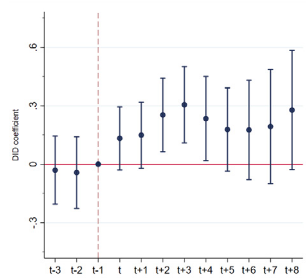
Dep. variable:	*LogPatFilings*					
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Post × Invo^{high}	0.136	0.211***	0.207**	0.226***	0.131	0.269***
	(0.086)	(0.080)	(0.087)	(0.080)	(0.130)	(0.104)
VC × Post	−0.031	−0.114*	−0.033	−0.065	0.031	−0.018
	(0.066)	(0.064)	(0.055)	(0.049)	(0.045)	(0.043)
Post × Invo^{high}	−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.	3741	3741	3713	3713	3741	3741

Panel B: Coefficient plots: Event study graphs

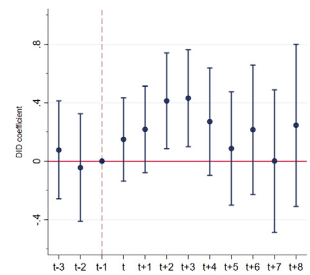
Invo^{high}: CVC



Invo^{high}: EXP



Invo^{high}: REP



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 Eq. (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.

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.

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 Eq. (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.

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

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	z 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.	1178	1176	1178	1094	1082	1094	1164	1154	1164
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	1000	988	1000	1620	1608	1620

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 Eq. (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.

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 approach is helpful as industry measures are likely unrelated to sample firms' business activities.

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 IA11 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.[13]

6. Conclusion

VCs are specialized financial intermediaries with several important roles in entrepreneurial processes, moving beyond the mere role of a

[13] The results are robust to adjustments in the definition of patenting intensity and using citation-weighted patent measures (Table IA13, Appendix). The enabling effects do not vary across sectors (Table IA14, Appendix).

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 characteristics 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.

CRediT authorship contribution statement

Andrej Gill: Writing – review & editing, Validation, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **David Heller:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Nina A. Michel:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.respol.2024.105060. It contains all additional estimation results and descriptive statistics that are referenced but not displayed in the manuscript, including tables (Appendix A) and figures (Appendix B).

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