Enabling or Accelerating? The Role of Venture Capital in the Innovation Life Cycle.

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This paper investigates how venture capital investors (VCs) affect the generation of intellectual property rights, such as patents, of their portfolio firms. Using a unique European dataset comprising firm-, patent-, and investment-level data on about 9.600 firms between 1995 and 2015, we assess four groups of firms distinguishing VC versus non-VC-backed and previously patenting versus non-patenting firms to establish the actual functioning of VCs. We deploy multiple econometric techniques to differentiate the (i) enabling and (ii) accelerating role of VCs: We find (i) previously non-patenting firms to increase patent quantity, while (ii) previously patenting firms increase patent quality. Our study provides new evidence on the role of VCs for firm-level innovation.

JEL Classification: D23; G24; L26; O32
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1 Introduction

For stimulating economic growth, it is essential to provide an environment that fosters innovative activities (e.g., Schumpeter 1942; King and Levine 1993). In this context, a sound financing environment is crucial, especially for young ventures (e.g., Carpenter and Petersen 2002; Robb and Robinson 2014; Hirsch and Walz 2019): These firms are particularly dynamic, featuring the highest growth rates, disruptive potential, and trigger important knowledge-spillovers, but their financing processes are accompanied by severe information asymmetries and uncertainty (e.g. Stiglitz and Weiss 1981; Binks and Ennew 1996; Schnitzer and Watzinger 2022). Venture capitalists (VCs) are specialized types of investors taking the leading role in the selection and financing of these firms, as they can alleviate agency issues through active involvement in the management (Amit *et al.* 1998; Berger and Udell 1998; Gompers and Lerner 1999; Hellmann and Puri 2002; Casamatta 2003; Krishnan *et al.* 2011; Bertoni *et al.* 2011). Following this, VCs should contribute largely to innovative processes of their targets.

However, empirical evidence on the role of VCs for fostering innovative activities, such as patenting, is ambiguous. Some studies suggest an enhancing effect of VCs on patenting firms, implying that target firms increase the amount of patents filed after the VC steps in (e.g., Mollica and Zingales 2007; Samila and Sorenson 2011; Bertoni and Tykvová 2012; Popov and Roosenboom 2012; Faria and Barbosa 2014; Kelly and Kim 2018). A second stream of the literature argues that VCs shift the focus of the target firm to sales as soon as the inventive process is completed, or merely pick successful targets instead of fostering innovative potential in the long-run. This push for rapid commercialization of their targets' innovation output leads to a decline in patented inventions after the initial VC investment (Engel and Keilbach 2007; Caselli *et al.* 2009; Peneder 2010; Arqué-Castells 2012). Hence, it appears that the role of VC in the innovation lifecycle is a priori not clear.

In this paper, we disentangle two fundamental roles of VC investors on the post-investment innovative performance of their target firms. In particular, we consider the two complementary roles of *enabling* and *accelerating* of VC investment on patenting output. We define enabling as the initiation of patenting activities of previously not patenting firms, whereas accelerating describes the post-investment change in patenting activities of firms that already patented before the VC stepped in. To detail this, we put a special emphasis on the exact timing of firms' patenting activities. Short-term effects of VC investments are unlikely to reflect true enabling or accelerating but rather reflect a change in the commercialization strategy of target firms. Hence, this paper aims to answer the question whether VCs can be considered as enablers, accelerators, or both.

Our final dataset comprises 9,614 firms from the EU15 countries in all relevant industries for a time-span of 21 years, starting in 1995. It combines firm-level balance sheet data (ORBIS) with information on individual rounds of VC investment (Refinitiv Eikon) and European patent data (PATSTAT). To estimate the effects of VC investments on post-investment patenting activities we follow a multi-stepped matching approach that provides us with comparison groups of non-VC backed counterparts for both previously patenting and non-patenting firms.

Our findings emphasize that it is indeed crucial to distinguish between an enabling and an accelerating role of VCs. More specifically, we find VCs to be enablers, that is to enhance the patenting activity of the target firms that have not filed for patents prior funding significantly. The instantaneous probability to file for a patent is 3.3 times higher for a VC funded firm relative to a comparable firm without funding. In contrast, we do not find an accelerating effect for the average firm that has patented before it received their first round of funding, compared to their non-funded counterparts.

Taking a closer look at the distinct timing of patent applications allows us to carve out further insights. For pre-VC non-patenting firms, we find both positive instantaneous and long-run effects. This suggests that the observed enabling effect comprises VCs that extract patents shortly after the initial round of funding as well as those reinforcing patenting activities in the long-term. This is different for pre-VC patenting firms, which do not change patenting activities, irrespective of the examined time frame.

Further, we exploit heterogeneity in VC involvement to highlight likely mechanisms behind the main results. We find the enabling effect to apply across investor characteristics suggesting that VC investors in general lift constraints to patenting that muted their targets patenting activities prior to the initial investment. Importantly, we also find that high investor involvement may indeed trigger an accelerating effect: Despite the absence of an accelerating effect in the average firm-investor relation, highly involved and more experienced investors add to their targets patenting productivity. Our findings thus provide novel evidence on the capabilities of highly specialized investors to enhance and accelerate patenting activities, even in cases in which targets have already a proven record of patenting activities prior to the engagement. Taken together, our results thus shed new light on the role of VC investors for firm-level patenting activities and deliver possible explanations on the mixed evidence in previous empirical analyses.

For several reasons, it is non-trivial to isolate the actual roles of VCs in the invention processes. First, we have to follow target firms along a fairly long part of their lifecycle, including the earliest stages after incorporation as well as several years after the initial VC investment. We overcome this issue by utilizing a combination of different data sources that allow us to document pre-investment activities and evaluate post-investment outcomes. Second, innovation dimensions need to be comparable across time to evaluate their development after the initial investment. We therefore choose to assess firm level patenting activity which is a relevant dimension of innovative performance for VC targets (Howell *et al.* 2020). Third, there are essential differences among patenting, non-patenting as well as ventures that eventually receive VC and those that do not receive these investments. To assess differences in the actual post-investment patenting behavior, we generate four groups of firms. We first distinguish targets that already patented prior to the initial VC investment and those that do not. Using Coarsened Exact Matching we then assign each of these firms a counterpart with comparable pre-investment observables (e.g. location, industry, age, size, and growth dynamics). Controlling for these covariates mitigates concerns regarding the endogenous decision of VCs whether to invest into a firm or not. To further reduce concerns that unobserved characteristics bias our results, we make use of a switching regression with endogenous switching (e.g., Chemmanur *et al.* 2011).

Our findings extend the literature on the effects of VC financing on firm dynamics and growth. Specifically, our analysis focuses on innovative performance as a driver of economic growth and uses patented inventions as one distinct dimension of it. Prior studies provide evidence for an enhancing effect of VC involvement on a variety of productivity-related firm performance indicators (e.g. Jain and Kini 1995; Manigart and Van Hyfte 1999; Burgel *et al.* 2000; Bottazzi and Da Rin 2002). VC financing plays a central role for innovative output, since it acts as a close substitute for firm-level R&D investments and encourages target firms to invest more consistently in in-house R&D (Kortum and Lerner, 2001; Da Rin and Penas, 2007; Hirukawa and Ueda, 2011). Our results provide important new insights to this debate as we distinguish pre-VC patenting and non-patenting firm cohorts, which is found to be an important difference in the VC financing process (e.g., Häussler *et al.* 2012). Taking a specifically granular view on the timing of firms' patenting activities after the initial investment, the analysis also shows that the differentiation both across pre-VC patenting activities and the exact timing of events is indeed important, as it leads to strikingly different outcomes. Taken together, our results provide one potential explanation for the ambiguity in the literature regarding the implications of VC investments on subsequent inventive activities.

These findings relate to an emerging strand of literature that combines observations from before and after the initial VC investment. For example, Baum and Silverman (2004) conclude that the role of VCs is a combination of scouting strong technology (selection) and coaching their target firms via management skills. This view, however, is not uncontested. As such, Colombo and Grilli (2010) find contradictory results only pointing towards a coaching function of the VC, whereas Peneder (2010) finds the positive effect of VC on innovation to be driven solely by a positive selection effect.[1] Our study specifically focuses on differences in patenting, as a consequence of VC investment, while controlling for differences in the selection process. On top of this, the detailed perspective on the timing of patenting activities allows us to distinguish the enabling and accelerating roles of VC investments in the short- and in the long-run.

The remainder of the paper is structured as follows. Chapter 2 presents our conceptual framework and introduces our dataset. Chapter 3 introduces the research design of enabling and accelerating and the baseline results. Chapter 4 and 5 look at the timing of the patenting behavior and underlying mechanisms respectively before we conclude in Chapter 6.

[1] Other studies do not find a significant selection or coaching effect at all (e.g., Arvanitis and Stucki 2014; Lahr and Mina 2016).

2 Conceptual Framework and Data

2.1 Concepts of Enabling and Accelerating

Enabling versus accelerating: The following subsection outlines the conceptual idea behind our analysis, which provides the basis for our empirical strategy. The average effect of VC investments on patenting activities, Δ_{avg}, intuitively equals the differences in patenting activities between firms with and without VC financing. More specifically, we decompose patenting activities of VC-backed and non-VC-backed firms, V and N) respectively, by comparing patenting activities before and after the VC-backed firms receive initial VC financing, i.e., $\delta_V = V_{post} - V_{pre}$. Analogously, changes in patenting activities of firms without VC-backing over the same period are given by $\delta_N = N_{post} - N_{pre}$.[2] In both cases, patenting outcomes are also affected by firm-, industry-, country-, and time-specific effects (X'), which, however, are likely to be the same for VC-backed and non-VC-backed firms. For simplicity, we therefore assume in the following that $X' = X'_V = X'_N$. Hence, Δ_{avg} is the average effect of VC investment on the patenting activity of VC-backed firms relative to firms without VC financing:

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

A priori, the properties of the average effects for firms with or without patenting activities prior to the initial VC investment are not clear. By definition, this effect cannot be negative for firms without any patenting activities. This illustrates that Equation (1) does not account for a crucial factor: The pre-VC patenting activity of firms. We thus distinguish the Δ_{avg} for pre-VC patenting and non-patenting firms. This differentiation delivers us with the two concepts of enabling and accelerating. More specifically, we define the *enabling* effect as the situation in which VC financing ignites patenting activities for firms without patenting activities prior to VC financing. In contrast, for ex ante patenting firms, the effect of VC investments on patenting outcomes can be positive, negative, or zero. We collectively refer to this as the *accelerating* effect.

[2] By definition, these firms do not receive VC at any point in time, such that the differentiation between pre and post VC is a conceptual idea, reflecting a hypothetical investment: Comparing pre- and post VC financing levels for a firm j that does not receive VC financing (N) refers to the situation in which an identical firm, i, actually receives VC financing.

This way, we follow the general consent in the literature ascertaining an enhancing effect of VC financing on firm-level productivity outcomes. Hence, the overall effect defined in Equation (1) can be re-written as:

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

which takes into account whether firms engage in patenting activities before initially receiving VC financing (1) or not (0). The average effect of receiving VC financing 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 financing round. Rearranging Equation (2) allows to test the effects of VC financing on patent outcomes, conditional on pre-VC patenting activities. Firms that do not receive VC (N) serve as a reference group, which is similarly affected by market developments. As illustrated in Panel A of Figure 1, firms thus can be categorized into the four groups: V^0, V^1, N^0, and N^1.

- Insert Figure 1 here -

For the enabling effect, the components V^0_{pre} and N^0_{pre} cancel out, since these two firm types do not patent prior to VC financing, i.e., $V^0_{pre} = N^0_{pre} = 0$. Panel B of Figure 1 illustrates the conceptual idea of the two main effects graphically. Following this, the *enabling* (Δ_{ena}) and *accelerating* (Δ_{acc}) effects are:

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

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

This conceptual framework suggests that the enabling and accelerating effects are mutually exclusive, implying that one single firm may not be subject to both effects. Moreover, the specific differences in pre-VC patenting activities ask for two separate analyses, applying two different estimation approaches.

The timing of the effects: As a last step, we incorporate timing considerations. In fact, Equations (3) and (4) are silent about any timing considerations. However, the actual timing of patenting activities is central for gaining a deeper insight on the actual role of VCs in the innovation life cycle of their targets. This is because patenting is a firm-level outcome that is the product of medium-termed inventive activities. Patents are typically filed at an earlier stage of the innovation process as compared to other realized property rights, such as trademarks (**?**). Still, patent applications are the results from time-intensive research and development in the past that realize over time. It follows that there should be a substantial time gap between the initial idea creation, the development of a patentable invention, and its final application. Hence, a patent application within the first year after the initial VC investment is unlikely to mark a technological invention that originated within this very first year. Instead, it is fairly likely that the development of this invention was already initiated prior to the VC investment.

The time gap between idea creation and patent application has important implications for our conceptual design. Consistent with the fact that average cycle times of new product lines take about 36 months (Griffin 1997; Cankurtaran *et al.* 2013), we assume that the development of an entirely new technology, which is eventually patented, takes on average at least two to three years. Consistent with this, we expect that the initial idea and research about a new technology of the average patent that was filed within the first years after initial VC investment already existed prior to the investment. Conversely, patents filed at a later stage after the investment are more likely to be based on ideas generated after the initial VC investment. Since any concrete thresholds might be erroneous our estimation approach rather looks at the evolution over time.

From a conceptual perspective, patenting activities therefore have to be interpreted differently depending on the actual timing of the patent filing relative to the investment date. Any change in patenting activities as defined in Equations (3) and (4) within the first years after VC investment is likely to reflect - at least in part - the commercialization effect described in the literature (e.g., Caselli *et al.* 2009; Arqué-Castells 2012; Lerner and Nanda 2020). This holds in particular for the first two years after VC investment. In this period, it is unlikely that any change in patenting activities reflects VC involvement that triggered idea creation of target firms. Changes in patenting activities right after the VC steps in can rather be expected to reflect a change in the exploitation strategy of existing ideas. Moreover, changes in patenting that result from the enabling or accelerating roles of VCs more directly should submerge on the medium term. For these reasons, only against the backdrop of the timing dimension, the roles of VC in firms' patenting activities can be evaluated.

2.2 Data

Data sources: Our sample contains data from mainly three sources. The basic firm-level financial and bibliographic data is obtained from Bureau van Dijk's ORBIS database, which covers the universe of firms from the majority of European countries. Because the coverage of distinct countries varies across time and in order to avoid selection biases, we collect data for the EU15 countries beginning with the year 1995.[3] We augment this information with detailed data on patenting and VC. Patent data is obtained from PATSTAT, which contains in-depth legal and other related properties covering the universe of patents filed in Europe. We extract VC data from the Refinitiv Eikon database, which provides detailed information on individual funding rounds per firm. We utilize these three sources to obtain four different groups of firms, which correspond to the groups V^0, V^1, N^0, and N^1 in Figure 1.

Matching approach: Our empirical analysis compares post-VC patenting across these four groups. However, whether or not a target firm receives VC investments is an endogenous decision by respective investors, i.e. it is plausible to assume that observable firm characteristics differ between VC targets and other firms. To mitigate concerns regarding these differences, we deploy a matching approach that links VC targets to firms with similar observable pre-investment characteristics.

Determining the pre-investment time window for firms that actually do not receive VC investments is non-trivial. In fact, the majority of firms does not receive VC at any point in time. To solve this, we first select those firm-year observations from non-VC-backed firms that

[3] The EU15 countries are the members of the European Union at the first sampling year: Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, and Sweden. We exclude Luxembourg because its economy primarily comprises financial firms.

can potentially be paired to VC recipients as they are equivalent with respect to the country of residence, industry affiliation (i.e., NACE main category), and founding year. On top of this, we impose that firms can only be paired depending on whether they have previously filed any patent application for any given calender year. This gives us a set of VC-backed and non-VC-backed, patenting and non-patenting firms that can potentially be paired. We thus match these firms, namely VC-backed and non-VC-backed firms, using Coarsened Exact Matching (CEM) according to pre-defined matching characteristics. We match based on firm size (log assets), asset growth, a more granular industry level (4-digit NACE), and the number of patents filed. For VC-backed patenting firms, these variables are computed for the average of the three years prior to initial VC investment. In contrast, for non-VC-backed firms, we compute these variables on the basis of three-year rolling windows. The matching procedure groups firms into stratas that may contain any number of VC-backed, non-VC-backed, patenting, or non-patenting firms. We only keep those stratas that comprise at least one VC-backed firm. To avoid heavily unbalanced group sizes, we select the closest non-VC-backed neighbor of any VC-backed firm within the respective stratas.

Following this procedure provides us with symmetrically-sized groups of patenting and non-patenting firms as defined in Equations (3) and (4), i.e. (V^0, N^0) and (V^1, N^1). Each firm has a matching partner that is comparable with respect to the location, industry, age, size, asset growth and pre-VC investment patenting activities. For non-VC-backed firms, the pre-VC investment period refers to the years before their matched VC-backed pair-firm receives financing for the first time. Table IA1 (Appendix) provides t-statistics on the matched sample. In line with our matching approach, there are no statistically significant differences among these groups along key observable characteristics before the initial VC round.

2.3 Sample Descriptives

The final data set contains 67,501 firm-year observations, comprising 9,614 individual firms. By construction, half of the sample receives VC funding at some point in time. Our sample covers 21 years (1995-2015) and we focus on firm-years spanning three years prior to the initial VC investment up until 10 years afterwards. Table 1 displays summary statistics on the key variables used in our sample. Table IA2 (Appendix) summarizes and defines all variables. The median sample firm is fairly young and small with an age of 7 years and a number of employees of 17.[4]

- Insert Table 1 here -

VC activity is concentrated on the largest economies in our sample, e.g., around 60% of the firm pairs are located in Germany, France, and the United Kingdom (see Panel B of Table 1). Regarding the sectoral distribution, our data set comprises firms from almost all industries. However, most observations are clustered in industries known for a high propensity to patent or to attract VC financing, such as information and communication (26%), manufacturing (21%), and professional, scientific and technical activities (20%). By construction VC funded and non-VC funded firms are equally distributed across industries. The distribution changes when only patenting firms are considered. Those firms are concentrated in manufacturing (46%) and professional, scientific and technical activities (32%).

Panel C of Table 1 displays some key facts among VC-backed firms with and without pre-VC patenting activities. VC targets with pre-investment patenting activities obtain more investment deals (1.8) compared to non-patenting counterparts (1.5). This difference is statistically significant but in economic terms rather small. Moreover, the difference in investment amounts collected during the initial VC round and overall are insignificant. This suggests that the firms in our sample are relatively similar, conditional on obtaining VC investment. These observations are consistent with the fact that VC select potential targets and focus on observable (i.e., patenting activities) as well as unobservable factors.

Figure 2 summarizes the patenting behavior of our sample firms, plotting the evolution of patenting relative to the initial VC investment date. Around 6% of those firms filed for at least one patent before the matching period t=0, which is by definition the same for VC-backed and non-backed firms. While overall 15% of firms eventually file at least one patent, this number is higher for VC-backed firms (18%) compared to non-VC-backed firms (12%). In Panel A, we compare the average VC-funded firms (V) and their non-backed matching partners (N), irrespective of their pre-VC patenting behavior. We find a significant difference between the

[4] At the time of the first VC investment, these median values are 4 years and 11 employees, respectively.

two groups concerning the number of patent applications in all years following the initial VC funding round. From this aggregate perspective it appears that the average VC-backed firm exhibits significantly higher patenting activities after the VC steps in compared to non-VC-backed comparison group.

- Insert Figure 2 here -

Descriptives, however, also show that it is important to consider the target firms' pre-VC patenting behavior. Specifically, in Panel B and C, we differentiate between patenters and non-patenters. First, Panel B assesses pre-VC non-patenting firms (V^0 and N^0). Here, we observe a strong wedge in the patenting behavior of VC-backed and non-backed firms with significantly more patenting filings by VC-backed firms. Second, Panel C compares the two groups of pre-VC patenting firms (V^1 and N^1). Here, we actually find no significant difference in the number of patent filings between the VC-backed group and the matched comparison group. Comparing the descriptive findings of Panel B and C emphasizes the need to take pre-VC patenting activities into account when analyzing the role of VCs for their targets' inventive activities.

3 Baseline Results

3.1 The enabling role of VCs

Estimation approach: The enabling effect equals the difference in post-VC patenting behavior of VC-backed firms relative to a comparison group without VC funding, conditional on not having any patents filed prior to the initial VC investment. To estimate the enabling effect empirically, we chose a survival analysis for estimating the effect of VC on the patenting activity of firms. In other words, the survival analysis compares the patenting activities of V^0 and N^0 in Equation (3). This approach has several advantages. First, we have to choose an estimation approach that does not rely on variation in pre-VC patenting activities. This is essential, because the pre-VC patenting activities of V^0 and N^0 are zero by definition. Moreover, the survival analysis addresses possible right-censoring problems inherent to firm-level panel datasets and is valid even if the timing of patent applications is not normally distributed across time, which is likely not to be the case in our setting. Specifically, we estimate the following Cox proportional hazard model:

$$h(t|x_j) = h_0(t)exp(\beta_1 VC_i + \beta_k X' + \alpha_{cs} + \alpha_{ct}) \;, \tag{5}$$

where i indexes firms, j indexes strata-specific years measured relative to the year in which VC-backed firms receive the first funding round, c indexes countries, s indexes industries and t indexes calender years. The hazard rate $h(t|x_j)$ 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 Cox proportional hazard model, i.e., the hazard can take any form in order to avoid misspecification. VC_i is a dummy variable which is equal to one for firms that receive VC funding and zero for firms from the comparison group. X' is a vector of control variables including the following observable, time-varying firm characteristics: total-debt-to-asset ratio ($DebtRatio$), firm size ($FirmSize$), profitability ($Profitability$), cash flow ($CashFlow$), and the share of tangible assets-to-total-assets ($Tangibiliy$). All variables are defined in Table IA2 (Appendix). Further, we control for general and country-specific macroeconomic fluctuations and firm-specific time trends by including α_{cs} and α_{ct} which are country-industry and country-calender year fixed-effects. The coefficient of interest is β_1, which reflects the differential average probability of a patent filing for VC-backed firms relative to their matched non-VC-backed comparison firms. In all estimations, we report standard errors clustered at the firm level.

Baseline results: To estimate the enabling effect as defined in Equation (5), we restructure our main sample of pre-VC non patenting firms to a firm-year panel starting with the first firm-pair year in which the VC target receives initial funding (t=0) and ending with the firm-specific year in which the respective firm files a patent application for the first time. We observe 10% of VC-funded firms to file for at least on patent after receiving the initial VC investment round in any subsequent observed period, whereas only 2% of non-VC-backed counterparts become patenters. Table 2 displays the results of the Cox regressions, which test this association in a multivariate setting using different combinations of fixed-effects, as indicated in the bottom of the table.

- Insert Table 2 here -

Column 1 displays estimates from the baseline model as specified in Equation (5), including the vector of control variables X' but without our set of fixed effects. The coefficient of VC_i is positive and significant on a 1% level and translates to a hazard rate of 3.3 which indicates that the instantaneous probability to file for a patent is c.p. 3.3 times higher for a VC-funded firm compared to the non-backed firm in the comparison group. In Column 2 we add country-industry and country-year fixed-effects. The coefficient of VC_i remains positive and significant and is robust to the inclusion. To rule out the possibility, that VCs enable their target firms to file for qualitatively inferior patents only, we deploy measures of patent quality in Columns 3 and 4. In Column 3, we use a citation-weighted patent filing count. In Column 4, we use the patent originality-score, which indicates not only patent quality but specifically refers to the breadth of technology fields on which a patent relies, thereby indicating the concepts of knowledge diversification (see Hall *et al.* 2001). The coefficient of interest remains significant and similar in size. In Column (5) we allow for multiple failures in order to address the concern that one time patenting could be random and our baseline results could be driven by those firms. The coefficient of VC_i still remains significant and positive and even increases in size. Taken together, the Cox model estimates show that VC-backed firms are associated with a much larger average probability to file for patents after the VC investment. This average effect is still persistent and even more pronounced when measures of patent quality instead of quantity are taken into account.

Figure 3 illustrates our findings. It displays the Nelson-Aalen cumulative hazard with regard to the probability of patent filings for the eight subsequent years after the initial VC investment for previously non-patenting firms. The difference between the two groups of firms is evident throughout the observed time span and widens over time. Further, Figures IA1 and IA2 in the Appendix exemplify that this pattern is stable when excluding firms that filed marginal patents that did not receive any citations or, as an alternative specification, when excluding firms with below-median citations.

- Insert Figure 3 here -

3.2 The accelerating role of VCs

Estimation approach: The key difference for estimating the accelerating effect as compared to the analysis of the enabling effect is that treated and non-treated firms (i.e., VC-backed and non-VC-backed firms) file at least one patent prior to the initial VC investment. Hence, the estimation approach has to take these activities into account in order to estimate the average accelerating effect of VC on the patenting activities of firms that already patented prior to the initial VC round, i.e., V^1 and N^1 in Equation (4). Since the data is structured in a panel with two comparable groups, one of which receives an investment (treatment) at some point whereas the other one remains without investment, we apply a difference-in-differences approach. Here, the first round of VC investment marks the treatment variable, whereas being a treated or a non-treated firm refers to the fact whether it eventually receives VC or whether it is a matched sample firm without VC financing. More specifically, our methodology follows previous work (e.g., Petersen 2009) by including a whole set of fixed-effects and adjusting the standard errors for correlations within clusters. In all estimations, we report standard errors clustered at the firm level. We estimate the following set of fixed-effects regressions for the matched sample of pre-VC patenting firms:

$$Y_{it} = \alpha_i + \alpha_j + \alpha_{ct} + \beta\,(VC_i \times post_{ij}) + \gamma' X_{ij} + \varepsilon_{ij}\ , \tag{6}$$

where all indexes are equivalent to Equation (5). The main dependent variable, Y_{ij} is the logarithm of the number of patent applications filed; α_i, α_j, and α_{ct} are firm, relative year, and country-calender year fixed-effects, X is a vector of control variables, identical to the control variables used in the survival analysis, and ε represents the error term. The interaction term $VC_i \times post_{ij}$ is equal to 1 if a firm receives VC funding for the first time in the firm-specific year j=0 and all subsequent periods and zero otherwise. VC_i is a dummy variable that is equal to one for any firm i that eventually receives VC financing and $post_{ij}$ represents a firm-specific dummy variable that equals one for all years after the initial VC investment is received by firm i. The main coefficient of interest is represented by β and captures the average additional effect of receiving VC on firms' patenting activities. β is positive if an accelerating effect through VC involvement exists. Importantly, we stack the data by defining the panel on the strata-specific basis of years relative to VC investment (j), i.e., not on a calender-year basis (t). This is advantageous, because treatment years are staggered across different years throughout the sample (see, Baker *et al.* 2022). Moreover, to avoid biased estimates in our two-way fixed-effects DID estimates, we follow the suggestion of Sun and Abraham (2021) and do not bin the earliest and latest periods (i.e., those more than 3 years prior or 8 years after the strata-specific VC investment year) but remove them from the estimations.

Baseline results: To test whether we can attribute VCs with an accelerating effect, we analyze the sample of pre-VC patenting firms. We observe 74% of VC-funded firms to remain patenters after receiving the initial VC round in any subsequent period that we observe, whereas only 64% of non-VC-backed counterparts continue patenting. This difference is statistically significant and robust to using different post-VC time windows.

To test this in a multivariate setting, we estimate Equation (6) capturing the effect of VC investments on their targets' patenting filings relative to the matched comparison group that did not receive VC. Results in Table 3 suggest that there are no differential patent filing activities after the VC investment between VC-backed and non-VC-backed firms. In particular, for our baseline regression the coefficient of the interaction term $VC \times Post$ is positive but statistically insignificant both with (Column 2) and without (Column 1) including a set of fixed-effects. The insignificant coefficient on the VC variable shows that on average there is also no difference prior to the first VC round, which confirms our matching approach.[5]

- Insert Table 3 here -

For robustness, we test this relationship in two alternative ways. First, it could be that the average patenting activity is not accelerated by VC involvement but temporarily VC involvement

[5]In undisplayed regressions, we can also show that results are consistent across different industries and when excluding crisis years (i.e., 2001, 2008, 2009). This mitigates concerns that unobserved industry- or time-specific factors account for our results.

indeed leads to a shift in patenting. To study this, in Column 3, we estimate the baseline specification but exchange the *Post*-dummy with an indicator that takes the value one only in the years 2-4 after the initial investment (*Med-Post*). This way, we can detect whether an accelerating effect temporarily unfolds but is not captured by the average *Post*-effect. The small and insignificant estimate in Column 3, however, rejects this notion.

Second, another explanation could be that VC investors do not enhance their targets patenting activities in quantitative terms but in terms of patent quality. We thus deploy the two measures of patent quality that have already been examined in the enabling context. Thus, in Column 4 we use the citation-weighted patent filing count and in Column 5 the patent originality-score, respectively. Again, using these two quality-related patenting measures does not change our results. In sum, our baseline results regarding the accelerating effect do not provide support for the idea that the average VC accelerates the patenting activities of pre-VC patenting targets.

4 The timing of post-investment patenting activities

4.1 The timing of the enabling effect

Methodology: To have a more detailed view on the timing of patent applications regarding the enabling effect, we employ a switching regression with endogenous switching as deployed in comparable analyses (Dunbar 1995; Fang 2005; Chemmanur *et al.* 2011). This method allows us to answer two hypothetical questions for each year following the initial VC investment: What would the patenting behavior of VC targets be, had they not received financing? And, vice versa, what would the patenting behavior of non-funded firms be had they received financing by a VC? Answering these questions on a year-to-year basis provides a very granular perspective on the enabling role of VC investors.

Formally, the switching regression with endogenous switching comprises two stages: 1) a two-step Heckman-type approach and 2) a prediction of the firm-outcome of interest (in our case patenting activities) across firms and time. Beginning with the Heckman-type estimations, we first 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 firm-specific variables that influence the decision whether a firm receives financing or not, including the following observable, time-varying firm characteristics: firm size ($FirmSize$), profitability ($Profitability$), total-debt-to-asset ratio ($DebtRatio$), the time (full years) since the incorporation date ($FirmAge$) and the share of tangible assets-to-total-assets ($Tangibiliy$). Deploying a dynamic probit model including relative-year, industry, and country fixed effects, Equation (7) predicts the probability to receive VC funding and yields consistent estimates of γ for previously non-patenting firms (V^0 and N^0). Then the inverse Mills ratio is computed, using the results that stem from the previous estimation.

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

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

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

Both Equations are estimated using OLS with either the number of patent filings ($LogPatFilings$), the number of forward citations ($CitsFilings$) or the average number of forward citations ($AvgCitsFilings$) as the dependent variable. Equation (8) estimates the effects after the initial round of funding for VC-backed firms while Equation (9) estimates the effect for the non-backed matching partners respectively.[6] Including the inverse Mills ratio from the first-step probit estimation as an additional regressor mitigates concerns that unobservable characteristics influence the selection of VC targets in the first place (see Dunbar 1995; Fang 2005; Chemmanur *et al.* 2011). After the OLS estimation we compute the hypothetical number of patent filings for VC-backed firms had they not received VC financing using Equation (8) and the hypothetical number of patent filings for non-VC-backed firms had they received VC financing using Equation

[6]Both equations can be consistently estimated using OLS when they are augmented with the inverse Mills ratio (see Maddala (1986) and Heckman (1979) for a detailed discussion).

(9) .

Comparing those predicted values with the actual values comprises the second stage of the switching regression with endogenous switching. This way, the above specifications allow us to answer the two "What-if" questions posed above. We compute the difference between the actual and the predicted number of filings separately for each year after initial funding to get an idea about the distinct timing of the enabling effect. Obtaining these figures annualy allows us to examine whether enabling only takes place in the short-run or whether VCs enable their target firms to increase their patenting activity in the long-run.

Results: Overall the results highlight a positive short- and long-term effect of VC involvement on quantitative as well as qualitative features of patenting. Panel A of Table 4 displays the estimates of our switching regressions on the number of patent applications each year after the initial round of funding (in logs.). Estimates for VC-backed firms show that the actual number of patent application is always higher than the predicted one. The difference between those two values is always negative and significant. Importantly, the enabling effect is present in the short- as well as in the long-run. In the first four years following the initial VC investment, the actual number of patent filings is around three times higher than the predicted number, had the companies not received financing. In the fourth to seventh year post funding, this difference becomes bigger and reaches the maximum value in the seventh year, in which the actual number of filings is five times higher than the predicted one. In line with our findings, the opposite is true for the non-backed comparison group: In the first year after a hypothetical funding, their hypothetical patent filing activity is estimated to be higher by a factor of five, had they received VC funding. Again, this difference is robust and significant on a one percent level for six subsequent years following a potential funding. Thus, the enabling effect of VCs on the patenting behavior of their target firms is consistent and significant over time.

Next, we confirm this finding for a qualitative feature of patenting. Panel B displays the actual values for the citation weighted count of the patent filings (in logs.) and compares them to the predicted values. The difference for firms that receive VC funding is negative and significant in all periods following the initial investment round, indicating that the quality of the patents would have been significantly worse, had the target firms not received VC backing. This difference is statistically significant at a one percent level for all observed years and widens until the seventh year post funding. The opposite is true and even more pronounced for the non-backed matching partners. Table AI2 in the Appendix confirms those finding with average patent citations.

- Insert Table 4 here -

Overall the switching regression adds insight on the distinct timing regarding the patenting behavior of our sample firms. The results highlight a positive short- and long-term effect of VC involvement on quantitative as well as qualitative features of patenting. This indicates, 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. Moreover, VCs have a significant positive effect on the quality of the patents their target firms file for.

4.2 The timing of the accelerating effect

Methodology: For assessing changes in pre-VC patenting firms inventive activities over time, we deploy event-study estimation techniques. By decomposing the treatment effect (i.e., β_1 from Equation 6) for each year in our data we can assess the post-investment changes in patenting on an annual basis. At the same time, the estimates on the pre-investment period serve as a robustness test on parallel trends in the patenting behavior between VC-backed and non-VC-backed firms from the comparison group. We estimate the following DID-estimation specification:

$$Y_{it} = \alpha_i' + \alpha_{ct}' + \alpha_j' + \sum_{S=-2}^{-3} \beta_1^S (VC_i \times Pre_{ij}^S) + \sum_{S=0}^{8} \beta_2^S (VC_i \times Post_{ij}^S) + \gamma' X_{ij} + \varepsilon_{ij}' \quad . \tag{10}$$

where Y_{ij}, X_{ij}, VC_i are specified equivalent to Equation (6); α_i', α_{ct}', and α_j' denote firm, country-year, and firm-specific time fixed-effects. Moreover, in Equation (10), we decompose the treatment indicator, $Post_{ij}$ on a year-by-year basis: $Post_{it}^S$ and Pre_j^S are equal to one (and zero otherwise) for all observations S years after or prior to initial VC investment, where $S = [0, 8]$ or $S = [-3, -2]$, respectively. The last year prior to the VC investment ($S = -1$) is the reference time period.

Results: Decomposing the accelerating effect over time, shows that there is no specific time trend in the years subsequent to the initial investment. Panel A of Figure 4 plots the event-study regression coefficients, $Post^S_{it}$ and Pre^S_j using the logarithm of patent filings as dependent variable. Estimates show that the insignificant average effects estimated in the baseline regressions is stable across all observed years. All coefficients are very comparable in size, while none of them is statistically different from zero. Moreover, we find VC-backed and comparison group firms to move in parallel trends prior to the initial investment. In Panel B, we find that these patterns are consistent when using quality-based patenting measures.[7] These findings suggest that there is no additional accelerating effect of VC investment on the patenting activities of firms that already patent prior to initial investment.

- Insert Figure 4 here -

5 Mechanisms and heterogeneous treatment effects

5.1 Patenting outcomes and investor involvement

In this section, we explore variation across firms to elicit underlying mechanisms behind these average treatment effects. Specifically, we investigate heterogeneity across VC investors and their relation to the strength of the enabling and accelerating effects of target firms' patenting activities. Our main idea is that stronger investor involvement should translate to firm-level patenting outcomes, given that VCs directly affect the patenting activities of firms.

Plausibly, direct investor involvement is hard to quantify in observational data. We measure differences in VC involvement using additional investor-level information from the Crunchbase database. To account for potential imperfections in the measurement approaches, we use three distinct ways to measure the degree of investor involvement. For robustness, we also test different

[7] In addition to this, we estimate the switching regressions for the subset of pre-VC patenting firms. Table X shows that there is statistically significant difference in the predicted number of patent filings and the actual number of patent filings for pre-VC patenting firms. This confirms previous findings in this section and adds to the validity of the findings in Section 4.1.

variants of these specifications.

As a first measure, we follow previous studies which find that target firms of corporate venture capitalists (CVCs) exhibit a particularly high degree of involvement, tolerance of failure, and technology know-how, all of which enhance the innovativeness in terms of patenting outcomes of their targets (e.g., Benson and Ziedonis 2010; Chemmanur *et al.* 2014). We measure corporate venture capital by flagging those investors that act both as investors and as the operating organization (CVC). Alternatively, we also use the CVC label provided for some firms by Crunchbase.

A caveat of studying CVCs is that there might be only relatively few targets that are actually backed by CVCs. Thus, we ground the remaining two measures on the fact that investor experience is a strong positive determinant for the degree of involvement of VC investors (see Bottazzi *et al.* (2008)).[8] As an approximation of the investor experience, we first follow literature by using the Crunchbase rank (RANK) as first objective measure of investor experience (e.g., Edwards and Todtenhaupt 2020). According to Crunchbase, the variable measures the number of connections of a profile within the platform.[9] Thus, the number of connections in the platform should increase with the VC investors activities, i.e., investor experience. For classification of the investment deals we consider both the average rank and the best rank of investors within one VC investment. Second, we estimate investor experience more directly by counting the number of investment deals an investor participated in (DEALS). We then compute both the average number of deals of all investors and the maximum number of deals of all investors participating in deals observed in our sample. To employ these these three measures of investor involvement in our analysis, we mark VC investments in which investors participate i) are CVCs or ii) that rank above median level of the overall experience distribution (RANK, DEALS) as high involvement deals ($\text{Invo}^{high} = 1$) and zero otherwise.

[8]There are also other determinants for investor involvement, in particular, target age (Bottazzi *et al.* 2008). However, since patenting and firm age are interdependent, we do not consider this specification in our analyses.

[9]Crunchbase uses proprietary algorithms to rank firms according to their importance. These connections include but are not limited to news articles, funding events, and acquisitions. The algorithms allow each of these connections to decay over time, such that ranks vary over time and are not only a function of investor age.

5.2 Heterogeneous treatment effects along investor involvement

5.2.1 Investor involvement and the enabling effect

We start by studying the effect of investor involvement as a source of heterogeneous effects regarding VCs' enabling potential of patenting. The previous sections demonstrated that there is an enabling effect of VC investments. We now study whether this average effect differs among firms that are backed by more or less involved investors as measured by the three VC characteristics CVC, RANK, and DEALS, as defined in Section 5.1. To do so, we modify the Cox regression specification from Equation (5), such that:

$$h(t|x_j) = h_0(t)exp(\beta_1 VC_{ij} + \beta_2 \text{Invo}_i^{high} + \beta_3 VC_{ij} \times \text{Invo}_i^{high} + \beta_k X' + \alpha_c + \alpha_j + \alpha_{ct}) \ , \quad (11)$$

where Invo^{high} is an indicator equal to one for firms that are backed by an investor with an above-median level of investor involvement and zero otherwise. The interaction of Invo^{high} and VC_{ij} captures the additional effect of particularly experienced investors on the instantaneous probability to patent of a VC-backed firm. Invo^{high} is equal to one for target firms with an highly involved investor according to the definitions outlined in Section 5.1. All remaining variables are specified as before.

Our findings emphasize that the expression of the enabling effect does not vary across CVC- and VC-backed firms or across different degrees of investor involvement. Table 5 displays the results from estimating Equation (11), using different specifications of Invo^{high}. Across all specifications, the coefficient of interest on the interaction term $VC \times \text{Invo}^{high}$ is positive, but statistically not significant. Hence, distinguishing among target firms that are backed by investors with relatively high and low involvement does not change the baseline estimates on the enabling effect (see Table 2). If anything, as the positive but insignificant results for all specifications suggest, firms with higher experienced investors also exhibit a larger enabling effect.

We show that this finding holds also when using an alternative empirical strategy. In particular, we estimate the cumulative hazard rates on the likelihood to patent over time. Illustrated in Panel B of Table 5, the hazards between the VC-backed firms with high and low involvement investors are not significantly different from each other throughout the observed timespan. While there is a slight positive and statistically significant difference after several years when using DEALS as a measure of involvement, this finding does not apply across specifications. Taken together, we do not find robust evidence that the average enabling effect differs among firms that are backed by more or less experienced investors. To interpret, these findings provide suggestive evidence that VC investors in general enable their targets to enhance targets patenting activities in the form of lifting constraints to patenting that muted respective targets patenting activities prior to the initial investment.

- Insert Table 5 here -

5.2.2 Investor involvement as a trigger for the accelerating effect

As a next step, we show that investor experience indeed has important implications for the accelerating effect, that is, for pre-VC patenting firms. While the *average* pre-VC patenting firm does not disproportionally respond to VC investment relative to the matched control group, this changes with the degree of involvement of the investor. More specifically, pre-VC patenting firms with experienced investors indeed benefit from more patenting outcomes. Consistent with the idea that involvement mirrors interest regarding the medium- to long-term performance of targets, these effects only unfold in the medium term, i.e., 2-4 years after the initial investment. To uncover this relationship we augment the DID regression specification from the main analyses as follows:

$$Y_{it} = \theta_i + \theta_j + \theta_{ct} + \beta' \left(VC_i \times post_{ij} \times Invo_i^{high}\right) + \vartheta' X_{ij} + \varepsilon_{ij} \ . \tag{12}$$

The regression specification is similar to Equation (6) but adds a triple interaction term of the DID interaction ($VC_i \times Post_j$) with the dummy variable Invo^{high}, which is defined as before. For consistency, the vector of control variables here also includes the single components of the triple interaction term that are not absorbed by fixed effects, i.e., the DID interaction ($VC_i \times Post_j$) and the interaction term $Post_j \times Invo^{high}$.

Table 6 contains the results from estimating Equation by using different specifications of Invo^{high} (see Columns 1, 3, and 5). Across specifications coefficients on the triple interaction term, β', are positive and sizable. Yet, the coefficients partly lack significance or are only weakly significant. At best, this suggests a moderate positive accelerating effect for firms that are backed by highly involved investors for the average post-investment period. As discussed in Section 4, the effects of VC on firms patenting activities may only unfold with a certain time lag. We therefore repeat the estimations but exchange the *Post* indicator with the *Med-Post* dummy which indicates the change in patenting 2-4 years after initial VC investment. Across all three specifications of investor involvement (Columns 2, 4, 6), coefficients on the triple interaction are positive and significant at the one percent level. These estimates suggest that there is indeed a positive accelerating effect of VC investors on their targets' patenting activities. This effect applies for firms conditional on i) having a high investor involvement and ii) only with a certain time lag after the initial investment.

- Insert Table 6 here -

To verify these findings, deploy event-study type regressions similar to those introduced in Section 4.2 but estimated on the subsample of firms subject to high investor involvement. For all three specifications of high investor involvement, we find consistent results: There is no immediate effect in patenting activities in the period of the initial VC investment. However, we obtain positive significant estimates on patenting activities over the course of the subsequent years, which reverts back to insignificant values by the fourth or fifth year after initial investment. These findings underscore the accelerating role of VC investors, conditional on exerting high involvement.

6 Conclusion

The financing environment is crucial for the performance and growth of young startups. VC investors are key players in the market of enterpreneurial financing. Literature attributes several important roles to VC investors moving beyond the mere role as a financier, such as selecting and mentoring targets. These roles should be particularly relevant in the context of inventive activities of the target firms. Yet, previous literature has provided mixed evidence when it comes to the question whether VC financing has an effect on inventive output, such as patents.

In this paper, we are the first to disentangle the enabling and accelerating role of VC investors. We thereby shed new light on the contradictory findings in previous literature on the effects of VCs on targets' patenting behavior. Specifically, we distinguish the effects of VCs on patenting by disentangling firms with and without patenting activities prior to the initial VC investment. Enabling and accelerating are mutually exclusive concepts, since VC can either enable pre-VC *non-patenting* firms' patenting activities or accelerate pre-VC *patenting* firms' patenting activities.

Our findings show that VCs act as enablers for firms, that have never been active patenters before they received funding. These portfolio firms file for significantly more patents than their non-funded counterparts and file fore patents that are significantly more relevant. For firms that have been patenters prior funding we find no accelerating effect. These findings emphasize the importance to consider differences on the firm-level to evaluate the role of VCs to affect the performance of their targets.

Furthermore, we assess the timing of these effects to obtain a better understanding on the enabling and accelerating roles. The key idea is that true enabling or accelerating should only become visible after some time. Yet, we find the enabling effect to appear right after the initial VC investment. This emphasizes that enabling appears to be a combination of selecting the target firm and pushing for rapid commercialization. Importantly, however, the enabling effect persists over time, which highlights that enabling moves beyond mere selection and commercialization motives but includes a long-term benefit of VC. Studying the timing of the effects also confirms the absence of an accelerating role for the average VC investor in the short- as well as in the long-run.

Our results show that VCs do not generally accelerate patenting activities of those target firms that already patent prior to their initial involvement. As a final step in our empirical analysis, however, we explore heterogeneity across VC investors to show that *highly involved* investors can indeed trigger an accelerating effect. That is, we show that investments by CVCs and more experienced VCs yields a positive medium-term effect on pre-VC patenting firms' inventive activities. This provides evidence on the capabilities of highly specialized investors to enhance patenting activities even in cases in which targets already have a proven record of patenting activities prior to the engagement.

Our results have important implications since they provide a more nuanced view on the role of VC investors in trajectories of their targets. VCs can indeed foster inventive activities, in particular, for those firms that previously did not generate inventive output or in the case of highly specialized VCs. Yet, this does not apply for all VCs and depends on underlying firm characteristics. Similarly, selection and commercialization motives appear to be important, since VCs ultimately want to maximize returns on their investments. From a research perspective, our results add to the understanding why prior literature on the overall effects of VC investment on their targets innovative output may lead to contradicting results.

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Tables from the main part

Table 1: Summary statistics

Panel A: Statistics on main variables

	Obs.	Mean	SD	Min.	Q25	Median	Q75	Max.
FirmAge	67,461	9.961	8.821	1	3	7	14	33
Empl	38,595	64.086	108.895	1	5	17	62	432
FirmSize	67,484	14.465	2.226	0.693	13.154	14.492	15.824	25.303
AssetGrowth	57,033	0.011	0.032	-0.044	-0.006	0.004	0.021	0.098
DebtRatio	67,370	0.607	0.375	0.040	0.320	0.589	0.838	1.529
Profitability	51,684	-0.052	0.286	-0.836	-0.101	0.015	0.098	0.351
CashFlow	46,034	-0.001	0.238	-0.649	-0.038	0.052	0.130	0.328
Tangibility	67,484	0.196	0.282	0	0.013	0.062	0.251	1
LogPatFilings	67,484	0.051	0.248	0	0	0	0	4.522
PatFilings	67,484	0.050	0.217	0	0	0	0	1

Panel B: Country and industry distributions

	Obs.	in %
France	2,582	26.86
Great Britain	1,852	19.26
Germany	1,230	12.79
Spain	746	7.76
Netherlands	636	6.62
Sweden	588	6.12
Other EU countries	1,980	20.59
Total	9,614	100.00

	Obs.	in %
Information & communication	2,540	26.42
Manufacturing	1,958	20.37
Scientific & technical activities	1,876	19.51
Wholesale/retail trade	1,100	11.44
Finance & insurance	622	6.47
Admin. & service activities	523	5.44
Other Industries	995	10.35
Total	9,614	100.00

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

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

Notes: The table provides summary statistics on the full sample. Panel A provides statistics on the key variables used in the analyses. All variables used are defined in Table IA1 (Appendix). Panel B displays the country and industry distribution of the sample. Panel C provides statistics on VC- and IPO related variables for sample firms that eventually receive VC funding, comparing pre-patenting and non-patenting firms as defined in the Section 2.1. Specifically, it displays information on the deal sizes in the first round and overall rounds (in million Euros) and the total number of deals received. Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

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

Dep. variable:	*TimeSinceVC*				
	(1)	(2)	(3)	(4)	(5)
VC	1.348***	1.354***	1.571***	1.362***	1.487***
	(0.155)	(0.157)	(0.316)	(0.243)	(0.187)
FirmSize	0.147***	0.133***	0.133**	0.092*	0.167***
	(0.025)	(0.028)	(0.049)	(0.044)	(0.028)
Profitability	-1.373***	-1.297***	-1.446***	-1.228***	-1.501***
	(0.166)	(0.167)	(0.302)	(0.258)	(0.149)
CashFlow	-0.009	-0.014	0.004	0.003	-0.013
	(0.007)	(0.011)	(0.003)	(0.002)	(0.014)
DebtRatio	0.006*	0.008*	-0.027	-0.013	-0.001
	(0.003)	(0.003)	(0.045)	(0.036)	(0.002)
FirmAge	-0.023**	-0.025**	-0.029	-0.040*	-0.035***
	(0.008)	(0.009)	(0.018)	(0.016)	(0.010)
Tangibility	-0.376	-0.817**	-2.077*	-1.557**	-0.832**
	(0.220)	(0.277)	(0.818)	(0.489)	(0.260)
Country-Industry FE	No	Yes	Yes	Yes	Yes
Country-Year FE	No	Yes	Yes	Yes	Yes
Obs	22857	22857	23391	23259	23956
Chi2	272	15029	13936	246899	4777596

Notes: In this table we present the results of our semiparametric survival approach. The dependent variable is the logarithm of the number of annual patent applications (Columns 1,2 and 5), citation-weighted patent applications (in logs) (Column 3) and the patent originality index as defined by Hall *et al.* (2001) (Column 4). The regression specifications follow Equation (5). All regressions include the binary variable VC, indicating whether a firm receives funding or not. Moreover we include a set of firm characteristics and several fixed-effects. The data in column (1)-(4) is set up such that firms drop out of the dataset after the first failure. Column (5) allows for multiple failures in order to address the concern that one time patenting could be random. Standard errors are clustered at the industry level (4-digit NACE). Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table 3: Assessing the Accelerating Effect (Pre-VC Patenters - matched sample)

Baseline difference-in-difference estimations

Dep. variable:	Patenting activities				
	(1)	(2)	(3)	(4)	(5)
VC × Post	0.044	0.052		-0.012	0.013
	(0.042)	(0.038)		(0.044)	(0.014)
VC	0.033				
	(0.029)				
Post	-0.109***				
	(0.031)				
VC × Med-post			0.015		
			(0.036)		
Dep. var. specification:	*LogPatFilings*			*CitsFilings*	*OriginalityAvg*
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	0.11	0.44	0.44	0.40	0.34
Obs.	4,503	4,503	4,503	4,503	4,503

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), citation-weighted patent applications (in logs) (Column 4) and the patent originality index as defined by Hall *et al.* (2001) (Column 5). The regression specifications follow Equation (6). In Column 1, firm- and relative-year fixed-effects are omitted. All variables are specified accordingly. Column 3 uses an alternative specification of the Post-variable, Med-post, which measures the impact of VC on patenting on a medium term time window and is equal to one only for the years 2, 3, and 4 years after the initial VC investment. The sample comprises VC-backed firms and their matched counterpart for all years [-3,8] before/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 level, respectively.

Table 4: Actual and Hypothetical Patent Filings and Patent Citations for VC vs. Non-VC-backed Firms without pre-VC patent filings

	Actual	Predicted	Differences in means	Actual	Predicted	Differences in means
	Patent Filings					
	VC-backed firms (V^0)			**Comparison group (N^0)**		
t=1	0.037	0.012	-0.025***	0.003	0.015	0.012***
t=2	0.040	0.013	-0.027***	0.006	0.016	0.009***
t=3	0.042	0.014	-0.028***	0.007	0.015	0.008***
t=4	0.049	0.014	-0.034***	0.009	0.016	0.016***
t=5	0.054	0.014	-0.039***	0.007	0.016	0.009***
t=6	0.057	0.015	-0.042***	0.006	0.016	0.009***
t=7	0.069	0.014	-0.054***	0.008	0.018	0.009**
t=8	0.043	0.014	-0.028***	0.009	0.018	0.008**
t=9	0.033	0.016	-0.017**	0.015	0.019	0.003
	Patent Citations					
	VC-backed firms (V^0)			**Comparison group (N^0)**		
t=1	0.054	0.011	-0.044***	0.004	0.364	0.012***
t=2	0.054	0.011	-0.043***	0.004	0.335	0.009***
t=3	0.060	0.012	-0.049***	0.009	0.314	0.008***
t=4	0.064	0.013	-0.051***	0.010	0.283	0.016***
t=5	0.068	0.014	-0.055***	0.007	0.256	0.009***
t=6	0.077	0.015	-0.063***	0.006	0.243	0.009***
t=7	0.081	0.015	-0.065***	0.008	0.223	0.009**
t=8	0.053	0.016	-0.036***	0.009	0.204	0.008**

Notes: This table reports the results from the second stage of an endogenous switching regression model, the associated "what-if" analysis. The dependent variable in the first stage (unreported) is whether or not a firm gets VC financing in a given year. The dependent variable in the second-stage regression (unreported) is the logarithm of the number of patent filings or the logarithm of the number of citations received in a time span of five years for a patent filed in a given year respectively. The independent variables in these regressions comprise the Inverse Mills Ratio from the first stage and all the independent variables and fixed-effects from the semiparametric survival analysis. Both panels report the actual value of the dependent variable, the hypothetical value, and the difference between actual and hypothetical values. Whenever indicated, *, **, and *** denote significance at the 5, 10, and 0.1 percent level, respectively.

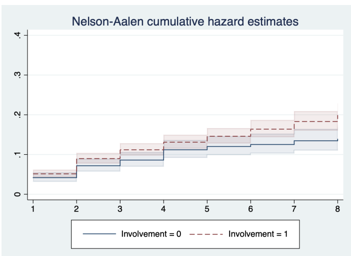
Table 5: Investor experience, involvement, and the Enabling Effect

Panel A: Cox estimations

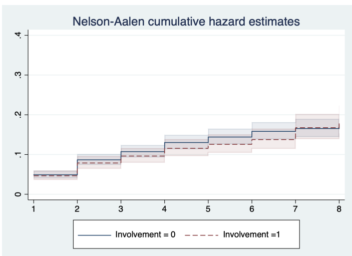
Dep. variable:	*LogPatFilings*					
	(1)	(2)	(3)	(4)	(5)	(6)
VC	1.311***	1.353***	1.310***	1.548***	1.277***	1.309***
	(0.164)	(0.289)	(0.164)	(0.215)	(0.169)	(0.217)
Invo^{high}	0.059	0.110	-0.049	0.437	-0.172	-0.110
	(0.131)	(0.315)	(0.118)	(0.290)	(0.116)	(0.294)
VC $\times$ Invo^{high}		-0.061		-0.576		-0.073
		(0.342)		(0.309)		(0.316)
Invo^{high} definition:	CVC		RANK		DEALS	
Country-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	20,285	20,285	20,285	20,285	18,834	18,834
Chi2	2414807	6.294e+09	220728	22367	4991	1394202

Panel B: Coefficient plots: High investor involvement and the enabling effect

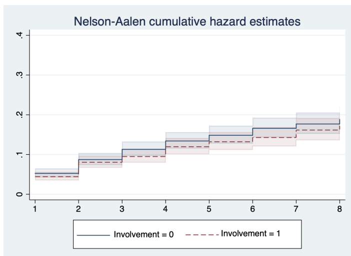
Invo^{high}: CVC



Invo^{high}: RANK



Invo^{high}: DEALS



Notes: Panel A shows the results of our extended semiparametric survival approach. All six models display Cox regressions with the left hand side representing the time since the initial round of VC financing. In columns (1) and (2) we distinguish between investor types. The regressions include an indicator variable that takes the value 1 if an investor involved is the investor as well as the operating organization and thus, a CVC. In column (3) and (4), investor experience is approximated by the rank of the investor. Thereby we consider investors that are ranked above median. In column (5) and (6) investor involvement is estimated by the number of investment deals. Thereby we use the full Crunchbase database and only our sample firms to determine deals, in which the average investor experience is above the median values. All regressions include the binary variable VC, indicating whether a firm receives funding or not. 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 level, respectively.

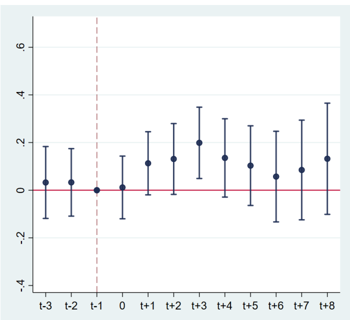
Table 6: Investor experience, involvement, and the Accelerating Effect

Panel A: Triple-Difference estimations

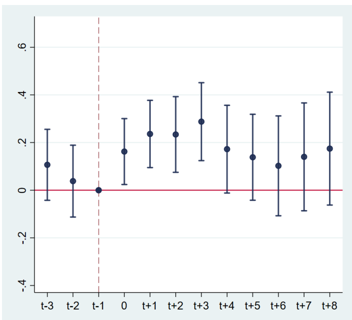
Dep. variable:	$LogPatFilings$					
Invo^{high} definition:	CVC		RANK		DEALS	
	(1)	(2)	(3)	(4)	(5)	(6)
VC × Post × Invo^{high}	0.136	0.211***	0.162*	0.201***	0.208**	0.226***
	(0.086)	(0.080)	(0.096)	(0.074)	(0.087)	(0.080)
VC × Post	-0.031	-0.115*	0.007	-0.093*	-0.033	-0.065
	(0.067)	(0.064)	(0.046)	(0.053)	(0.055)	(0.049)
Post × Invo^{high}	-0.046	-0.015	0.025	0.001	-0.004	-0.071
	(0.053)	(0.052)	(0.066)	(0.046)	(0.056)	(0.048)
Post definition:	Post	Med-post	Post	Med-post	Post	Med-post
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.46	0.46	0.46	0.46	0.46	0.46
Obs.	3,741	3,741	3,741	3,741	3,713	3,713

Panel B: Coefficient plots: High investor involvement and the Accelerating Effect

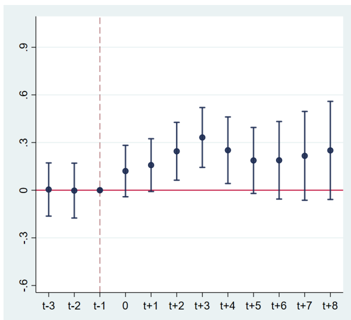
Invo^{high}: CVC



Invo^{high}: RANK



Invo^{high}: DEALS

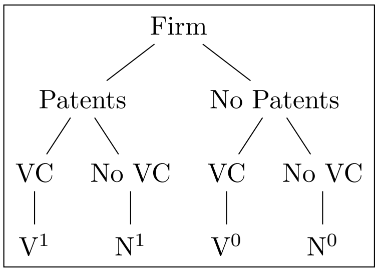


Notes:

Figures from the main part

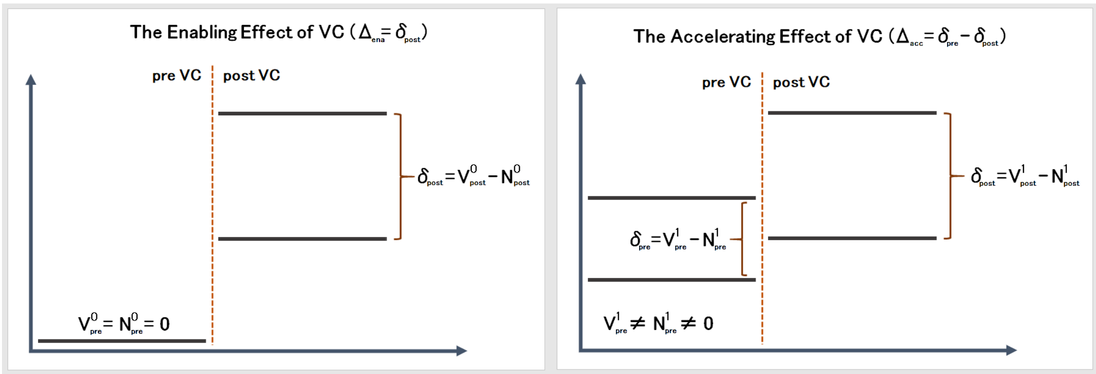
Figure 1: Graphical illustrations of the conceptual framework

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



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

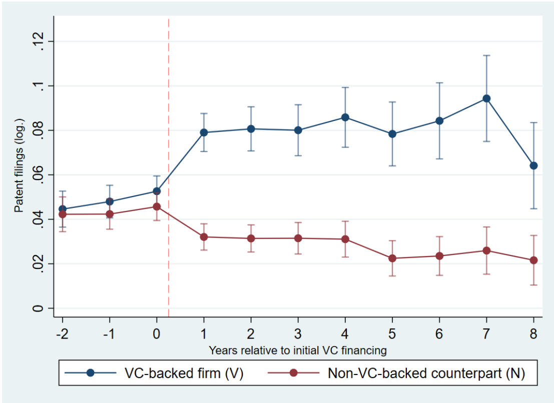
Panel B: Illustrating the Enabling and Accelerating Effects of VC



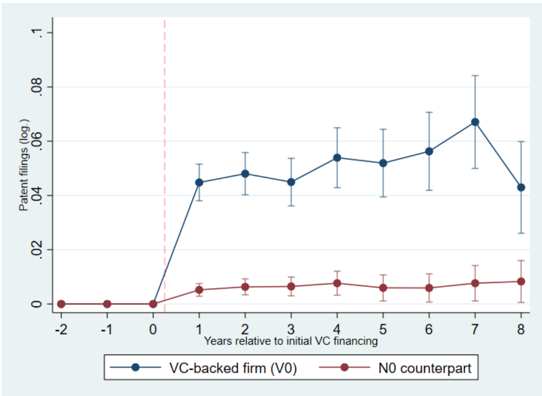
Notes: These Figures illustrate conceptually the methodological framework of our empicial strategy. Panel A illustrates graphically how we distinguish the different firm types relevant for our conceptual framework, as outlined in section 2.1. Panel B is a graphical illustration of the two main effects, the enabling and the accelerating effect of VCs, as described in section 2.1.

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

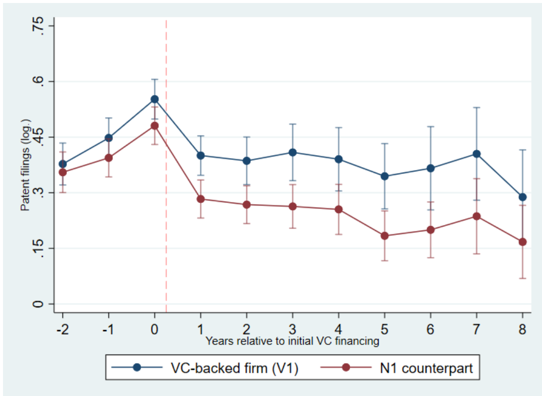
Panel A: All firms



Panel B: Pre-VC non-patenting firms

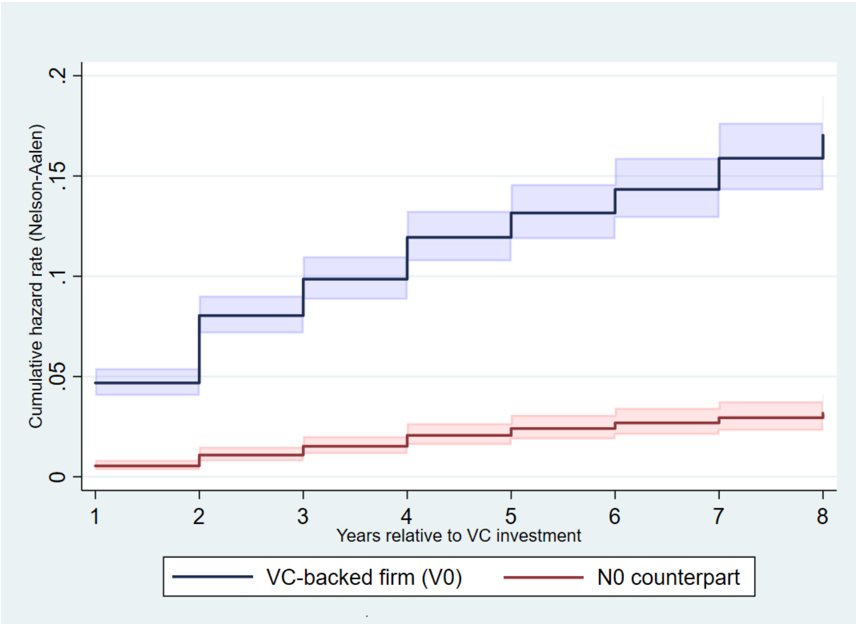


Panel C: Pre-VC patenting firms



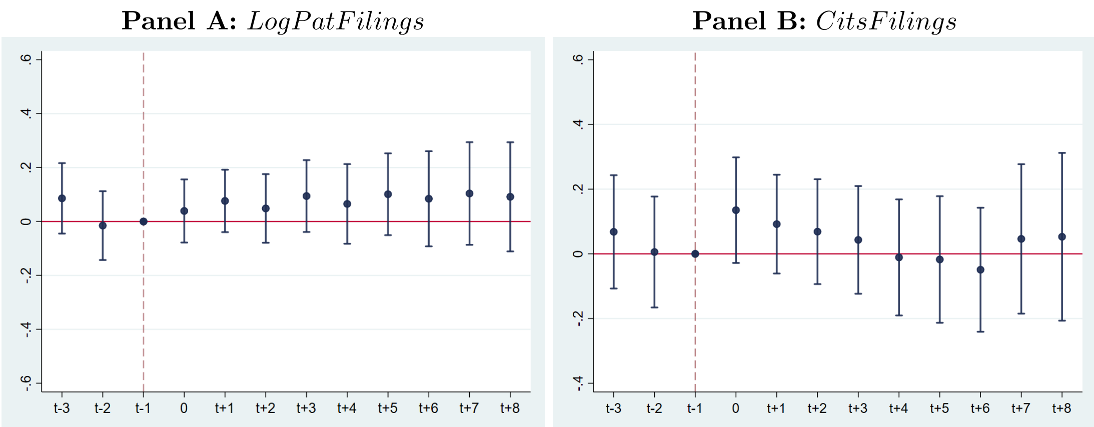
Notes: These Figures examine the potential enabling and accelerating effect as defined in 2.1. Panel A displays the logarithm of patent applications each year for firms that have not filed patents before the initial round of funding and for their non-backed counterparts two years before and eight years following the first funding. Panel B displays the logarithm of patent applications each year for firms that have filed patents before the initial round of funding and for their non-backed counterparts in the same time-span.

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



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

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



Notes: The figure plots coefficients of the event-study-type regression from Equation (10). The dependent variable in Panel A is the logarithm of patent filings and in Panel B the logarithm of citation weighted filings as defined in Table IA2 (Appendix). Both panels display the DID-coefficients that interact year-dummies with the VC-indicator. Years are denoted to the strata-specific relative years to the initial VC investment. Whiskers span the 95 percent confidence intervals.

FOR ONLINE PUBLICATION

Internet Appendix A : Tables

Table IA1: Comparing matched sample groups during pre-VC phase

Panel A: Firms *without* pre-VC patent filings

	VC-backed (V/N)		Differences in means
	V^0	N^0	
FirmSize	13.689	13.657	0.032
FirmAge	7.689	7.673	0.016
AssetGrowth	1.110	1.107	0.003
CurrentRatio	1.728	1.775	-0.047
PatFilings	0	0	0

Panel B: Firms *with* pre-VC patent filings

	VC-backed (V/N)		Differences in means
	V^1	N^1	
FirmSize	13.924	14.036	-0.113
FirmAge	7.814	7.790	0.024
AssetGrowth	1.117	1.102	0.015
CurrentRatio	1.968	1.953	0.015
PatFilings	0.805	0.699	0.106
LogPatFilings	0.670	0.613	0.056
RecencyTop1	0.044	0.016	0.027^{*}
RecencyTop25	0.566	0.519	0.047
OriginalityAvg	0.337	0.350	-0.013
OriginalityMax	0.382	0.391	-0.009

Notes: The table provides summary statistics on financial and patenting variables for the five pre-VC years. The table compares the firm groups as defined in Section 2.1. Specifically, Panel A (B) compares firms without (with) patenting activities prior to initial VC investment using the average of the two pre-VC investment years. Further each table reports the mean values for those firms that eventually receive VC financing to those that do not. For the latter, the initial VC investment year is an artificial year as calculated in our matching procedure (see Section 2.2). Firm-level financial variables include information on size (measured as the logarithm of total assets), age, asset growth and are defined in Table IA2 (Appendix). Whenever indicated, *, **, and *** denote significance at the 10, 5, and 1 percent level, respectively.

Table IA2: List of variables

Key variables:	
VC	Dummy = 1 if the firm receives venture capital at any point in time and zero for matched comparison group firms.
post	Dummy = 1 for any firm-specific year j after the initial VC investment(within matched strata) and zero otherwise.
Med-post	Dummy = 1 for any firm-specific years J ($\in$ [2,4]) after the initial VC investment(within matched strata) and zero otherwise.
Pre^S	Dummy = 1 for any firm-specific year S ($\in$ [-3,-2]) before the initial VC investment (within matched strata) and zero otherwise.
$Post^S$	Dummy = 1 for any firm-specific year S ($\in$ [0,8]) after the initial VC investment (within matched strata) and zero otherwise.
$Invo^{high}$	Dummy = 1 for any VC-backed firm that is financed by a highly-involved VC specified as indicated by any of the three criteria CVC, $RANK$, or $DEALS$ respectively, and zero otherwise.
TimeSinceVC	Time elapsed since initial VC investment of VC-backed firm or of matched comparison group partner for non-VC-backed firms.
LogPatFilings	Logarithm of total patent filings within a year (main dep. variable).
Main control variables (Orbis code):	
DebtRatio	Total-debt-to-asset ratio (`loan`+`cred`+`ltdb`)/`toas`.
FirmSize	Logarithm of total assets (`toas`).
Profitability	Return on assets; earnings before interest and taxes (`ebit`) divided by total assets (`toas`).
CashFlow	Total cash flow (`cf`) scaled by total assets (`toas`).
Tangibility	Share of fixed tangible assets (`tfas`) over total assets (`toas`).
FirmAge	Time (full years) since incorporation date (`Date_of_incorporation`) and the balance sheet reporting date (`Closing_date`).

(*continued on next page*)

Table IA1: List of variables (*continued*)

Other variables (Orbis code):	
AssetGrowth	Year-to-year growth in total assets (`D.toas/L.toas`).
CurrentRatio	Liquidity risk; total current assets (`cuas`) over current liabilities (`culi`).
PatFilings	Dummy = 1 for any firm-year in which a firm filed at least one patent and zero otherwise.
CitsFilings	Logarithm of 1+citations received by patent over patent filing, with citations counted within the first five years after filing.
AvgCitsFilings	Average number of citations received by patent over patent filing, with citations counted within the first five years after filing.
RecencyTop1	Dummy = 1 if firms file at least one patent in the top 1 percentile of the recency distribution; where recency is defined as the average time lapsed between the filing of the focal patent and the referenced patents (in the backward references).
RecencyTop25	Dummy = 1 if firms file at least one patent in the top quartile of the recency distribution and zero otherwise.
OriginalityAvg	The average originality score of patents filed within a given year; originality refers to the breadth of a patent as defined in Hall *et al.* (2001).
OriginalityMax	The maximum originality score of patents filed within a given year.
CVC	Dummy = 1 for any target firm that is backed by a corporate venture capitalist; with two alternative specifications: i) VC that act both as investors and as organization and ii) VCs labeled as CVC by Crunchbase.
RANK	Dummy = 1 for any target firm that is backed by a VC with high experience, measured by the Crunchbase RANK, which is derived by the activity of VCs on the Crunchbase platform; High RANK are firms with an above median rank.
DEALS	Dummy = 1 for any target firm that is backed by a VC with high experience, measured by the number of deals the VC participated in. High experience are firms with above median number of previous investments.

Table IA3: Actual and Hypothetical Patent Filings and Patent Citations for VC vs. Non-VC-backed Firms with pre-VC patent filings

	Actual	**Predicted**	**Differences in means**	**Actual**	**Predicted**	**Differences in means**
	Patent Filings					
	VC-backed firms (V^1)			**Comparison group (N^1)**		
t=1	0.395	0.361	-0.034	0.291	0.392	0.100***
t=2	0.365	0.365	-0.000	0.279	0.386	0.106***
t=3	0.401	0.368	-0.033	0.260	0.380	0.119***
t=4	0.415	0.375	-0.040	0.278	0.385	0.107***
t=5	0.387	0.370	-0.017	0.201	0.375	0.375***
t=6	0.389	0.329	-0.059	0.217	0.343	0.125***
t=7	0.406	0.327	-0.079	0.279	0.322	0.0432
t=8	0.297	0.290	-0.006	0.170	0.304	0.134**
t=9	0.433	0.288	-0.144	0.193	0.280	0.086
	Patent Citations					
	VC-backed firms (V^1)			**Comparison group (N^1)**		
t=1	0.527	0.355	-0.171***	0.317	0.477	0.160***
t=2	0.520	0.328	-0.192***	0.235	0.457	0.223***
t=3	0.578	0.321	-0.256***	0.319	0.424	0.104*
t=4	0.552	0.304	-0.247***	0.337	0.431	0.094
t=5	0.463	0.267	-0.197**	0.241	0.373	0.132*
t=6	0.417	0.221	-0.196**	0.233	0.321	0.088
t=7	0.475	0.191	-0.284***	0.309	0.296	-0.013
t=8	0.404	0.141	-0.263**	0.284	0.241	-0.043

Notes: This table reports the results from the second stage of an endogenous switching regression model, the associated "what-if" analysis, for firms with pre-VC patent filings. The dependent variable in the first stage (unreported) is whether or not a firm gets VC financing in a given year. The dependent variable in the second-stage regression (unreported) is the logarithm of the number of patent filings or the logarithm of the number of citations received in a time span of five years for a patent filed in a given year respectively. The independent variables in these regressions comprise the Inverse Mills Ratio from the first stage and all the independent variables and fixed-effects from the semiparametric survival analysis. Both panels report the actual value of the dependent variable, the hypothetical value, and the difference between actual and hypothetical values. Whenever indicated, *, **, and *** denote significance at the 5, 10, and 0.1 percent level, respectively.

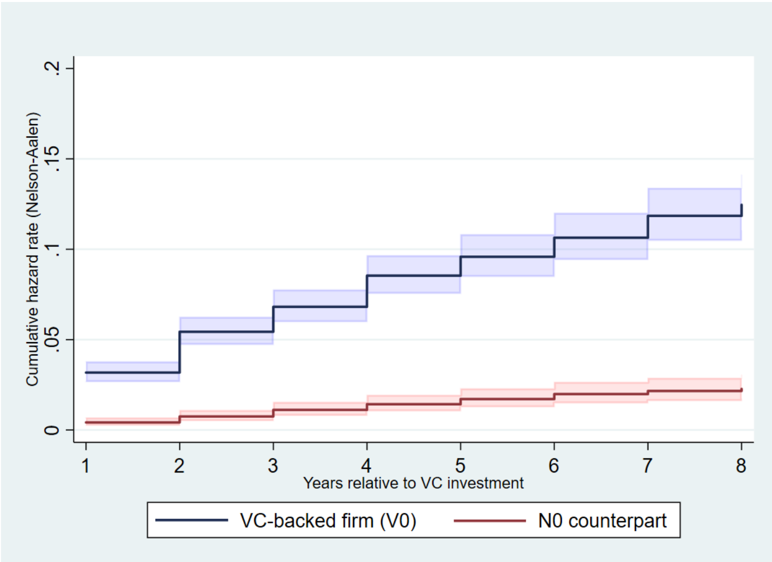
Table IA4: Actual and Predicted Average Patent Citations for VC vs. Non-VC-backed Firms

	Actual Avg. Citations	**Predicted Avg. Citations**	**Differences in means**
Panel A: Funded firms *without* pre-VC patent filings			
Filings in t=1	0.160	0.016	-0.145***
Filings in t=2	0.153	0.017	-0.136***
Filings in t=3	0.156	0.018	-0.138***
Filings in t=4	0.154	0.020	-0.134***
Filings in t=5	0.207	0.022	-0.186***
Filings in t=6	0.148	0.024	-0.125***
Filings in t=7	0.145	0.025	-0.120***
Filings in t=8	0.098	0.027	-0.071***
Filings in t=9	0.105	0.028	-0.076**
Panel B: Non-funded firms *without* pre-VC patent filings			
Filings in t=1	0.008	1.351	1.343***
Filings in t=2	0.006	1.240	1.234***
Filings in t=3	0.014	1.161	1.146***
Filings in t=4	0.018	1.038	1.019***
Filings in t=5	0.010	0.934	0.924***
Filings in t=6	0.007	0.883	0.877***
Filings in t=7	0.804	0.804	0.791***
Filings in t=8	0.008	0.733	0.724***
Filings in t=9	0.014	0.649	0.635***
Panel C: Funded firms *with* pre-VC patent filings			
Filings in t=1	1.522	1.247	-0.275
Filings in t=2	1.101	1.151	0.050
Filings in t=3	1.327	1.130	-0.196
Filings in t=4	1.128	1.049	-0.079
Filings in t=5	0.799	0.928	0.129
Filings in t=6	0.604	0.852	0.248
Filings in t=7	1.299	0.762	-0.536
Filings in t=8	1.015	0.622	-0.394
Filings in t=9	0.843	0.510	-0.333
Panel D: Non-funded firms *with* pre-VC patent filings			
Filings in t=1	0.611	1.117	0.506***
Filings in t=2	0.481	1.125	0.644***
Filings in t=3	0.794	1.087	0.293
Filings in t=4	0.913	1.088	0.175
Filings in t=5	0.447	1.026	0.579***
Filings in t=6	0.372	0.852	0.480***
Filings in t=7	0.948	0.791	-0.158
Filings in t=8	0.894	0.731	-0.163
Filings in t=9	0.391	0.682	0.291

Notes: This table reports the results from the second stage of an endogenous switching regression model, the associated "what-if" analysis. The dependent variable in the first stage (unreported) is whether or not a firm gets VC financing in a given year (VC Dummy). The dependent variable in the second-stage regression (unreported) is the average number of citations received in a time-span of five years for a patent filed in the respective year after funding. The independent variables in these regressions comprise the Inverse Mills Ratio from the first stage and all the independent variables and fixed-effects from the semiparametric survival analysis. Panel A reports the results of the "what analysis" for VC funded firms that have not filed for a patent before the initial round of funding, Panel B displays results for the non-backed counterparts. Panel C shows the results for VC funded firms that have been actively patenting before the funding, Panel D for their non-backed counterparts. All Panels report the actual average number of citations received in a time-span of five years for a patent filed in the respective year after funding, the hypothetical number, and the difference between the actual und the hypothetical values. Whenever indicated, *, **, and *** denote significance at the 5, 10, and 0.1 percent level, respectively.

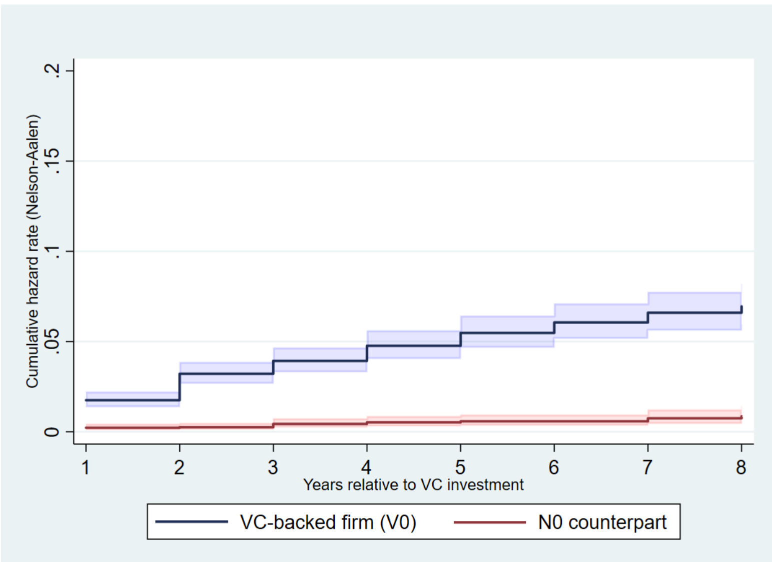
Internet Appendix B : Figures

Table IA1: Non-Patenters: Cumulative hazard estimates for patents that received at least one citation



Notes: This graph displays the Nelson-Aalen cumulative hazard estimates for the treatment versus control group. The treatment group comprises firms that have received VC funding but did not file patents before the initial round of funding, while their non-backed comprise the control group. Firms drop out of the dataset right after they filed their first patent. These estimations only include patents that have received at least one citation in the five years following the application and can thus be refered to as patents with impact.

Table IA2: Non-Patenters: Cumulative hazard estimates for patents that received more than medium citations



Notes: This graph displays the Nelson-Aalen cumulative hazard estimates for the treatment versus control group. The treatment group comprises firms that have received VC funding but did not file patents before the initial round of funding, while their non-backed comprise the control group. Firms drop out of the dataset right after they filed their first patent. These estimations only include patents that have received more than medium citations in the five years following the application and can thus be refered to as patents with high impact.