UNCOVERING THE IMPACT OF VENTURE CAPITAL FIRMS ON STARTUP INNOVATION

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RESEARCH ABSTRACT

I seek to uncover the effect of venture capital (VC) on innovation by studying which VC firms foster the startup innovative process, and in what context. I argue that specialist VC firms have the knowledge to help the startup innovate faster, but that this effect is moderated by context: the research environment of the country where the startup innovates is both complements and substitutes the main effect. I find empirical support from a sample of 923 VC-backed biotech startups from 26 countries during a period of high growth of the biotech industry (1996–2006). The results suggest that selection is not the main driver. Qualitative insights from interviews with 18 VC partners shed further light on the mechanisms underlying the effect of VC on innovation.

Keywords: startup, venture capital, innovation, specialist VC, country research environment.

> *People outside of this world probably think VC equals VC equals VC, and they don't realize how different they can be. We are different, we are asset shapers. We create a product. We look at what is out there, just like they [other VC firms] do, but we pivot the idea, we turn it around in different dimensions, and create something that was better than the initial product.*
>
> — Interview with a specialist venture capitalist

> *We are not involved in R&D. We just don't have the capabilities. We help with legal, contracts, marketing and sales, hiring, but we don't do R&D. That part is up to them [the startup].*
>
> — Interview with a generalist venture capitalist

INTRODUCTION

Ever since Schumpeter's seminal *Theory of Economic Development* (1934), startups have been regarded as an essential source of innovation and therefore as a pillar of technological progress. And yet startup innovation is fraught with challenges, for startups face the lengthy, costly, and risky process of innovation with fewer resources. The challenges are extreme in the life-sciences industry. With global health care costs at $7.7 trillion in 2017 and expected to rise to over $10 trillion in 2022 (Deloitte, 2019), and with pharmaceutical firms being manifestly slow to innovate, the industry relies heavily on startup innovation (Kessel, 2011; Krieger, Li, and Papanikolaou, 2019). The conundrum is that we need biotech startups to innovate in an industry where approving a new drug takes more than 15 years and over $1 billion (Kessel, 2011).

Investors may be able to help startups overcome some of the obstacles that arise in the innovation process, hence increasing their chances of success. Venture capital (VC) firms are of particular interest because they have a significant impact on economic growth through the financing of innovative startups (Gornall and Strebulaev, 2015; Samila and Sorenson, 2011; Timmons and Bygrave, 1986), and their contribution to startups goes well beyond merely financing (e.g., Gorman and Sahlman, 1989; Hellmann and Puri, 2002; Hsu, 2006). Kortum and Lerner (2000) provided the first empirical proof that VC investment was associated with higher levels of patenting, after accounting for the entrepreneurial opportunities and technological advancements in each industry. The effect is economically very significant: with 3 percent of R&D investment, VC investments amount to 8 percent of patents in the U.S. (Kortum and Lerner, 2000). Samila and Sorenson (2011) further support the impact of VC on innovation. They show that the supply of VC in a region fosters startup patenting not only directly, but also indirectly by enhancing the effect of research grants. These studies jointly provide empirical proof that VC firms, on average, foster startup innovation at an early stage above and beyond selection.

And yet, VC firms are far from homogeneous. As the two opening quotes reveal, the strategy of VC firms' involvement in startup innovation can vary significantly from one VC firm to the next (e.g., Gompers, 1996; Guler and Guillén, 2010). Importantly, we know that the level of active involvement in a startup can vary greatly across VC firms (Bottazzi, Da Rin, and Hellmann, 2008). We also know that the impact of VC firms is contingent on the context; for instance, the home-country status of foreign VC firms has an impact on startup performance, but that impact depends on the interconnectedness of the home and host countries, and their relative position in the global network (Alvarez-Garrido and Guler, 2018).

In this paper, I leverage the heterogeneity of VC firms, seeking to demonstrate which types of VC firms, and under which conditions, impact startup innovation at an early stage (i.e., startup patents),[1] and by doing so I seek to uncover the mechanisms by which this impact is achieved. I leverage a significant strategic choice made by VC firms: namely, whether they

[1] In this paper I refer to innovation, rather than invention, because ultimately I am interested in the process that will lead to the commercialization and definition of value. The literature uses both the term invention (e.g., Nerkar and Shane, 2007; Toh and Polidoro, 2013) and innovation (e.g., Ahuja and Katila, 2001; Berry, 2014; Fabrizio and Thomas, 2012) to refer to the early stage of innovation, as measured by patents. The stream of literature this paper builds upon has consistently used the term innovation (Alvarez-Garrido and Dushnitsky, 2016; Cox-Pahnke, Katila, and Eisenhardt, 2015; Kortum and Lerner, 2000), which I therefore use here for congruency.

invest broadly across industries or specialize in an industry. Indeed, VC firms categorize themselves as being *generalist*, when they do not restrict the industries they will invest in, or *specialist*, when they invest a larger size of their portfolio in a specific industry. I argue that specialist VC firms have a deeper understanding of the innovation the startups pursue, and find that they are associated with a higher level of startup patenting. While it is likely that both selection and treatment mechanisms are at play, in the empirics I seek to separate these effects with both quantitative and qualitative data.

I then argue that the extent to which specialist VC firms may foster startup innovation is not independent of the research environment of the country in which the startup innovates. I hypothesize that the country research environment is both a complement and a substitute to the effect of VC specialization on startup innovation—a complement because specialist VC firms leverage the research environment to help startups innovate, and a substitute because biotech startups can also leverage the research environment to find the help they need, and because VC firms prefer not to intervene unless it is necessary. I argue, and find, that specialist VC firms foster startup innovation more in research environments that are neither strong (which would lead to substitution) nor weak (which would preclude complementarity).

The biotechnology industry is an ideal setting in which to test the impact of VC firms on startup innovation. This is because patents are a clear measure of biotech startup innovation—patents are required to protect the product—but also because of how the process of innovation typically unfolds. In biotech, this process can be roughly divided into two stages: first, the translation of science—from basic science in the university lab, to applied science—culminating in a patent; second, the development of a drug that can be commercialized, requiring lengthy and costly clinical trials. Patenting is therefore an important and relatively early milestone in the innovation process. While startups and their investors want the innovation process to move fast to reduce the costs, patenting before the innovation is ready to continue its process would reduce the profit. I take advantage of this characteristic of biotech innovation and study the time to patent as a measure of startup innovation in the early stages.

My sample consists of 923 biotechnology VC-backed startups from 26 countries, observed from 1996 through 2006—a period of accelerated growth for the global biotechnology industry, coinciding with the revolutionary Human Genome Project. As a result of the industry's growth in this period, at different rates across countries, both VC specialization and the strength of the country research environment are heterogeneous in this sample. At the time the VC firm invested, 494 startups did not yet have a patent. This allows me to study the time to the startup's first patent, when the startup does not have experience and therefore external effects can be more readily identified.

I find that VC specialization leads to faster patenting. I also find that this effect is contingent on the strength of the country research environment: the effect of VC specialization on startup patenting is significant for moderate-level country research environments, but is not significant for country research environments that are weak (which would preclude complementarity) or strong (which would lead to substitution). The results are economically significant. A highly specialized VC firm boosts the speed to patent by 40 percent on average relative to a generalist with biotech experience and by 90 percent when the country research environment is moderate. To assess whether these effects are driven mostly by selection or by treatment, I further study whether specialist VC firms tend to select startups with a patent. The results show that this is not the case, hence reducing the concern that selection is driving the effects.

Uncovering the mechanisms underlying these effects requires additional insight. I conducted 18 interviews with venture capitalists with different strategies, across 7 countries.[2] The interviews reveal that some specialist VC firms select what I call *fixer-uppers*: startups that are not strong in all dimensions, and hence are less costly, but that the specialist VC firm can help fix. The interviews point to two treatment mechanisms by which specialist VC firms foster startup innovation. Specialist VC firms can help startups overcome what I call the *value translation problem*, or how to translate the science into an innovation that has the potential to generate revenue. They can also help startups overcome the *regulatory problem*, or how to structure the innovation process from the start, so that all scientific tests conducted can be used in the drug development (i.e., regulatory) process. Data from the interviews is also consistent with the role of the research environment both as complement and as a substitute.

This paper seeks to contribute to the innovation and entrepreneurship literature that studies the contribution of investors to startup innovation (Alvarez-Garrido and Dushnitsky, 2013, 2016; Cox-Pahnke *et al.*, 2015; Kortum and Lerner, 2000; Samila and Sorenson, 2010). More generally, the paper adds to the broader entrepreneurship literature that studies the contributions of VC firms to startups (e.g., Alvarez-Garrido and Guler, 2018; Gorman and Sahlman, 1989; Hellmann and Puri, 2002; Hsu, 2006). The paper also seeks to contribute to practice, by providing insight to three groups: to startups, on the strategic choice of selecting an investor and on when that investor may have the potential to contribute; to investors, on when the strategic choice of specialization in an industry pays off, enabling them to possibly better balance the trade-offs implied in choosing to specialize; and finally to policy-makers, on understanding which VC firms, and in which locations, foster startup innovation.

[2] Because in some countries a limited number of VC firms specialize in biotech, and to avoid identification, I only disclose only the VC firm's strategy, not its country.

THEORY DEVELOPMENT

Specialist and generalist VC firms

While most VC firms seek to provide business advice to startups to foster startup performance (e.g., Gorman and Sahlman, 1989; Hellmann and Puri, 2002), not all VC firms are equipped to provide technical advice that can foster startup innovation. In order to unveil the mechanisms by which VC firms impact startup innovation, the first step is to understand which specific VC firms can have a greater effect on that process.

One of the most important strategic decisions that VC firms make is what type of startup to invest in. When the VC firm raises a fund, the scope of the investment is defined along three dimensions: geographic (e.g., a country or a region); the stage at which to invest (e.g., early stage or series A); and whether or not the investment is restricted to a specific industry. In this paper, I focus on this last dimension, which is highly strategic in that it is long-term and difficult to change. Indeed, VC firms categorize themselves as being *generalist*, when they do not restrict the industries they will invest in, or *specialist*, when they invest most of their portfolio in a specific industry.

The decision to specialize in an industry is strategic because it requires hiring a dedicated team of experts for that industry. The venture capitalists I interviewed often referred to the importance of having a team with technical experience, as shown in the quotes below.

> *In our team everyone has a degree that has to do with life sciences. This is very important because the investments in health care are difficult, you need to speak the same language as the scientists do, you need to be able to ask the right questions.* (Interview with a specialist venture capitalist)

> *And I have great people . . . they are all scientists. . . An investor in biotech with people who have previously worked for McKinsey is going to be very different from an investor in biotech whose people previously worked for GSK [GlaxoSmithKline].* (Interview with a specialist venture capitalist)

Both selection and treatment mechanisms could drive the relationship between VC specialization and startup innovation. We know that VC firms strive to select promising startups that show promise (e.g., Amit, Glosten, and Muller, 1990; Baum and Silverman, 2004) and that startups prefer high-status VC firms (Hsu, 2004). Therefore, there is an association between quality startups and high-status VC firms (Sørensen, 2007). Startup quality is hard to assess, especially in the early rounds of investment, when there is very little information. Patents, which are coveted resources in themselves, are a signal of quality (Hsu and Ziedonis, 2013), but in the very early stages the startup may not have yet patented, and VC firms rely on less observable signals of quality. It is possible that specialist VC firms are better at selecting the most innovative startups because they have the industry experience to identify the elements required for startup innovation; specialist VC firms could also be preferred by the most promising startups. Therefore, selection of the most promising startups is the first mechanism in the link between VC specialization and startup innovation.

In addition to selection, VC specialization may have a treatment effect on the startup innovative process. Indeed, industry specialization is strongly related to how active the VC firm is—what venture capitalists call being hands-on (*versus* hands-off). Bottazzi *et al.* (2008) found that the industry experience of venture capitalists was related to how often they interacted with the startup and how active they were in helping the startup recruit the management team, set up the board of directors, or raise additional funds. My interviews suggest that specialist VC firms tend to be more hands-on. Compare the following two quotes by venture capitalists with different strategies:

> *We are very generalist. We don't invest in a particular industry, we invest across industries. We are not hands-on. We invest and, unless there is a problem, we don't intervene.* (Interview with a generalist venture capitalist)

> *All specialist VC firms are hands-on, because otherwise how are you going to help the startups in which you invest with the specific knowledge you have accumulated? Generalist VC firms are more hands-off.* (Interview with a specialist venture capitalist)

This second quote points to the competitive advantage of a specialist VC firm: it can provide more advice and guidance to the startup. Several different mechanisms could lead to an effect of VC specialization on the startup innovative process. We know that VC firms foster the commercialization alliances of startups (Hsu, 2006), and therefore it is possible that specialist VC firms use similar mechanisms to foster startup innovation. We know that VC firms provide consulting advice (Gorman and Sahlman, 1989), and therefore specialist VC firms may provide advice that is more targeted to the innovative process, hence fostering startup innovation. We know who the VC firm knows matters (Hochberg, Ljungqvist, and Lu, 2007), and specialist VC firms are likely to have a network of contacts—industry experts and other startups and large corporations in the industry—that they can tap into, in turn fostering startup innovation.

VC firms, generalist and specialist alike, have developed capabilities to select startups that show promise (Amit, Brander, and Zott, 1998; Amit *et al.*, 1990). The effect on the startup's innovation process may, therefore, be manifested more by the speed at which the innovation actually happens. As one interviewee explained:

> *What VCs do is create for them [startups] a sense of urgency and help them focus. . . And this helps the relevance and the speed of the innovation.* (Interview with a specialist venture capitalist)

Innovating fast is important throughout industries, but critical in biotechnology, where it takes on average 15 years to develop a drug (Kessel, 2011). Put simply, faster innovation lowers costs. I argue that the help of investors translates into a faster process of innovation and therefore a faster time to patent. I focus specifically on the first patent of a startup, because arguably the startup has less experience and the effect is more likely driven by external help, from the investors among others. Patents are a crucial milestone in the innovation process, and patenting fast most likely indicates that the innovation process is advancing in the right direction.[3] Therefore, I hypothesize,

Hypothesis 1. The startup's time to first patent decreases with VC specialization.

While Hypothesis 1 includes both selection and treatment, I seek to identify quantitatively which is the main driver of the results. Further, I capitalize on insights from qualitative data to shed light on the underlying mechanisms of both selection and treatment effects.

Research environment: A complement and a substitute

While up to this point I leveraged VC firm heterogeneity to investigate which VC firms can foster startup innovation, here I leverage context heterogeneity to assess in which context such an effect is more likely. Because both specialist VC firms and startups need to access external resources, I focus on the startup's country research environment and argue that it can be both a complement and a substitute to the effect of VC specialization.

Unlike corporate VC firms, which can tap into the complementary assets of the corporation that funds them (Alvarez-Garrido and Dushnitsky, 2016), VC firms do not possess the complementary assets required to nurture the technological innovation of the startup. Resources in the external environment are, therefore, more relevant to specialist VC firms in order to help startups in their portfolio innovate. Likewise, startups rely more than established

[3] One could argue that since patents signal quality, some startups could patent earlier than would be recommended to attract investors. Even though examining the performance consequences of faster patenting is not the goal of this paper, I do not believe this is true of biotechnology. The venture capitalists I interviewed explained that patenting worldwide (a must in biotechnology) is not only very expensive, but starts the count of 20 years of exclusive protection, and so investors have an interest in patenting when the innovation can continue to the next phase, and not earlier. Also note that even if startups wanted to patent to signal quality before a VC firm invests, the quality signal of a patent would be less valuable after the VC firm invests.

firms on external resources to balance the lack of internal resources (Eisenhardt and Schoonhoven, 1996; Pfeffer and Salancik, 1978).

The strength of the research environment of the country where the startup innovates is relevant, because it provides access to external resources that can be valuable, both to startups and specialist VC firms, to foster the startup innovative process. The importance of knowledge spillovers and access to experts cannot be overestimated. The literature has demonstrated the relevance of human capital in industry clusters (e.g., Alcácer and Zhao, 2012; Delgado, Porter, and Stern, 2010, 2016; Fallick, Fleischman, and Rebitzer, 2006; Saxenian, 1996, 2007); indeed, a supply of skilled labor is essential for the establishment of clusters around the world (Bresnahan, Gambardella, and Saxenian, 2001). The mobility of employees from startups to large corporations is also an important mechanism for such spillovers and has spurred entrepreneurship and innovation (Agarwal *et al.*, 2004; Campbell *et al.*, 2012). A strong research environment in a given industry requires the presence of innovators and supporting human capital that the startup can leverage, and it has been shown to foster entrepreneurship (Sarkar *et al.*, 2006). While geographic proximity matters, we know that the political borders of countries are, in the long term, difficult to overcome (Singh and Marx, 2013). Language, regulation, and access to grants are other factors that make country boundaries important in accessing resources from the research environment that can add value to the innovative process.

I argue that the relationship between the country research environment, VC firm specialization and startup innovation is complex. When the startup is located in a weak country research environment, there are fewer resources the specialist VC firm can tap into and therefore fewer tools to help the startup innovate faster. Because of this complementarity, I predict that the effect of VC specialization on startup innovation is higher for stronger country research environments. When the startup is located in a strong country research environment, however, the startup has abundant resources to tap into, and therefore the help that the specialist VC can provide is less exceptional, and hence less valuable. In addition, specialist VC firms may choose to be more hands-off, because it is costly for them to give advice. A venture capitalist I interviewed referred to the cost of being hands-on; with two people—out of a total of seven on staff—whose job is to advise startups, they prefer not to intervene unless necessary:

> *We have two people whose job is to be in touch with the ventures and help them. Ideally, we would like them to work on their own and not have to intervene. But this is rarely the case.* (Interview with a specialist venture capitalist)

Because in a strong research environment the startup can more easily access resources from the environment without the help of the specialist VC, and because the specialist VC prefers that the startup does so if it can, I expect a substitution effect: the effect of VC specialization on startup innovation should be lower for stronger country research environments.

Jointly, these complementarity and substitution effects predict an inverted-U-shape effect. The effect of VC specialization on startup innovation should be observed for country research environments that are neither too weak (so that the specialist VC firm cannot leverage external resources) nor too strong (so that the help of the specialist VC firm is no longer required). Therefore, I hypothesize:

> *Hypothesis 2. The startup's time to first patent decreases with VC specialization when the country research environment is moderate.*

DATA AND METHODS

Sample and interviews

The sample consists of 923 biotechnology startups from 26 countries. Because the goal of this paper is to assess the effect of VC industry specialization on startup innovation, all startups in the sample are VC-backed, and therefore the effect of VC industry specialization is in addition to the effect of VC-backing—*versus* non-VC-backing—on startup innovation studied in extant literature (e.g., Cox-Pahnke *et al.*, 2015; Kortum and Lerner, 2000; Popov and Roosenboom, 2012; Samila and Sorenson, 2010). Startups in the sample are observed from 1996 through 2006 (with patents observed up to 2011). This was a period of accelerated growth for the global biotechnology industry, coinciding with the revolutionary Human Genome Project, which in 1996 took off with the pilot test of DNA sequencing, soon after expanding into an international collaboration effort that led to the full sequencing of the human genome in 2003 (NHGRI, 2018).

Biotechnology startups as a research setting for this study offer a clean measure for their early-stage innovation—i.e., patents—allowing me to analyze the effect of VC industry specialization on the innovation process at its onset. Patents are critical because they provide intellectual property protection and are therefore a necessary step in developing any commercial application in biotechnology. Patents are also a strong signal of quality in the biotech industry (Hsu and Ziedonis, 2013), quality that needs to be demonstrated to investors in later rounds to raise the funding that the expensive product development requires.

The 26 countries included in the sample are representative of the biotechnology industry as a whole, and include almost all of the countries that had biotechnology patents during the study's window of observation. Spanning all five continents, the countries are Australia, Austria, Belgium, Brazil, Canada, Denmark, Finland, France, Germany, Hungary, India, Ireland, Israel, Italy, Japan, Malaysia, Netherlands, Norway, Portugal, Republic of Korea, South Africa, Spain, Sweden, Switzerland, United Kingdom, and the United States. The variation in the strength of the country research environment is not just cross-sectional, but also longitudinal, exploiting the changes in the biotechnology industry over time as it experienced accelerated growth.

The sample of biotechnology startups and their investors was collected from the VentureXpert database (Thomson Venture Economics)—a widely used database in entrepreneurship research (e.g., Cox-Pahnke *et al.*, 2015; Guler and Guillén, 2010; Shane and Stuart, 2002). For each startup, I collected information on all the investors, and for each investor, on its complete investment history (as recorded by VentureXpert). This information was necessary to compute VC specialization. This initial database was hand-matched to other sources, a process that required 2,500 hours by 31 research assistants over 7 years. These hand-matched sources included startup websites (or the Internet Archive, when the website was no longer available), news about these startups in Factiva, scientific publications in Web of Knowledge, and patents from the U.S. Patent and Trademark Office (USPTO).

In addition to the quantitative data, I conducted interviews with venture capitalists. The goal was to shed light on the mechanisms of selection and treatment, that is, to reveal a range of possible mechanisms and not to determine the most plausible mechanisms, much in the spirit of Siggelkow's talking pig (Siggelkow, 2007). With that goal in mind, I selected cases with theoretical variation, conducting a total of 18 interviews (nine with generalist VC firms and nine with specialist VC firms) in seven countries.[4] In almost all instances I interviewed VC partners, who are responsible for the strategic direction of the VC firm. Interviews were in person, in English, and between 30 and 60 minutes. They were semi-structured,[5] because the goal was to obtain rich qualitative information that would shed light on the mechanisms behind the effect of VC firms on startup innovation.

[4] The countries, selected to provide variation in the strength of the research environment, were Czech Republic, France, Germany, Israel, Spain, UK, and US.

[5] I first asked interviewees to introduce their VC firm and their investment objectives. Then I asked about the reason behind their strategy (generalist or specialist) and about how specifically they help the startup, and whether they contribute to startup innovation. I closed with follow-up questions that arose during the interview.

Empirical strategy

The empirical strategy leverages the quantitative information to test the effect of VC specialization on the startup's speed to first patent, followed by supplementary analyses to assess whether the effect is mainly driven by selection. To shed light on the mechanisms driving the effect, and on the selection *versus* treatment question, I complement this information with qualitative information from my interviews.

Two research decisions are important to provide a clean test—i.e., free of confounders—for the effect of VC specialization on startup innovation. The first is to focus on the first patent of the biotechnology startup, when the startup has arguably less experience in the innovative process. The second is to focus on the first VC firm, which the industry terms the lead investor, because the first investor tends to be more involved in the startup (more hands-on) in the very early phases (i.e., seed stage), as the quote below shows.

> *We are a series A investor, even though we can go earlier or later if needed . . . And we do not do this [be hands-on], it is not profitable for us, it takes too much of our time and it will not pay off, so we don't do this. At least not with healthcare. With macrobiomes, we have to do it [be hands-on] . . . But we are investing at seed stage, and it is very early for the industry, so we are making an investment long term. So for macrobiomes we are more hands-on. But otherwise, we are very hands-off.* (Interview with a specialist venture capitalist)

First, I focus on the 494 startups that had no patents at time of first VC investment and study whether VC specialization has an impact on the time to first patent. Of the 494 startups, half do patent before the end of the window of observation; the other half are right-censored. A hazard model is the best estimation method for this dependent variable and data structure (Allison, 1984, 1995). I estimate a Cox model, a semi-parametric analysis that does not impose a distribution on the underlying hazard. To study the moderating effect of the country research environment, I follow the recommendation of Shaver (2019) and split the sample by the level of country research environment.

The first set of analyses estimates the startup's time to first patent, which is of course conditional on the startup not having a patent when the VC firm first invests. Because patents are a signal of quality (Hsu and Ziedonis, 2013), the presence of sample selection bias must be assessed. Thus, the second set of analyses estimates a logit model on the full sample at the time of first investment, to assess whether VC specialization predicts whether the startup had at least one patent at time of investment. This analysis provides an indication of whether the results are mostly driven by selection or by treatment.

Dependent variables

For the Cox regression models, I define the event variable *Startup first patent after VC investment* as 1 if the startup has applied for at least one patent after VC investment and before the window of observation for the study, and 0 otherwise. The *Time to first patent after VC investment* is measured as the number of days between first VC investment and first patent application. Measuring in days helps avoid event ties in the sample (only 8% of cases), which improves the estimation power of hazard models. The second set of models seeks to assess sample selection bias. The dependent variable *Startup first patent before VC investment* is 1 if the startup has applied for at least one patent at the time of the first VC investment, and 0 otherwise.

Patents were hand-collected from the USPTO website, with hand-matching of the name of the company, location, and when necessary the scientists. Following the standard in the literature, I assume patents that are eventually granted, but at the time of application (Hall, Jaffe, and Trajtenberg, 2005; Jaffe, Trajtenberg, and Henderson, 1993). Because biotechnology is a global industry, startups need to patent in the U.S. system, and in all other major world markets, to protect their innovation and commercialize their product in that system (e.g., Almeida, 1996;

Furman, Porter, and Stern, 2002; Qian, 2007; Singh, 2007). Interviewees confirmed this fact on several occasions. In the words of a U.S. patent attorney interviewee specializing in biotech, “Most [biotech] firms file [patents] in the U.S. even if they are international firms.”

Independent variables

I measure *VC life-sciences specialization* as the proportion of VC firm investments (i.e., deals) in the life-sciences industry relative to the number of investments in all industries. This is calculated for the first VC firm that invests in the startup. When more than one VC firm invests in the first round (what the industry terms a syndicate of investors), it is reasonable to assume that the VC firm with the highest degree of life-sciences specialization would have a greater impact on the startup’s innovative processes. Therefore, when there is more than one VC firm in the first round of investment, the measure takes the maximum value.

The source of the information is VentureXpert. I gathered the complete investment history for all investors in each startup, and I then calculate the number of investments in life sciences and the number of investments across all industries, up to the time the VC invests in the startup. Because I want the specialization measure to reflect the current capabilities of the VC firm, I only consider the 15 years prior to the investment in the startup.

This measure is grounded in my interviews with venture capitalists, who told me they consider themselves specialists in an industry when most of their investments are in that industry. Technically, a low specialization value may indicate that the VC firm is either a generalist or a specialist in a different industry. However, because biotechnology is complex and investments need to be large and take a long time, it would be rare for a specialist in a different industry to venture to do an opportunity in biotech, and hence the control group is mostly generalists.

The variable *Country life-sciences patent stock* measures the country research environment of a startup. This variable follows Chung and Yeaple's (2008) measure of a discounted stock of patents. To calculate this measure, I gathered all biotechnology patents for each country-year directly from the USPTO, following the OECD's definition of biotechnology codes within the International Patent Classification system. To assess how the strength of the country research environment moderates the impact of *VC life-sciences specialization* on the *Time to first patent after VC investment*, I split the sample in three—following the recommendation by Shaver (2019)–using the 33^{th} and 66^{th} percentiles, into *weak*, *moderate*, and *strong* levels of *Country life-sciences patent stock.*

Controls

I further control for the characteristics of the VC firm with *VC experience,* which measures the VC firm's number of investments in all industries (e.g., Hsu, 2004, 2006; Sørensen, 2007). This controls for the effect of experience on performance, a well-understood mechanism in strategy scholarship. This variable is also the level (i.e., the denominator) for the main independent variable, *VC life-sciences specialization*. The unit of analysis is 100 investments. As explained above, the data source is VentureXpert, and the previous 15 years were considered.

Two additional country controls are included. The variable *Country investment in R&D/GDP* proxies for the depth of research in the country across all industries. The variable *Country GDP per capita* proxies for the potential for capital accumulation, capital that could potentially be invested in startups or research. The unit is $10,000 constant USD. Both measures are from the World Bank's World Development Indicators.

Additional controls on the startup itself are included. The variable *Startup capital* measures the capital that investors have invested in the startup (e.g., Guler, 2007; Hsu, 2006).

VC has a direct impact on startup innovation by funding such innovation and therefore should be controlled for. The data source is VentureXpert, and the unit is $100,000 USD.

The variable *Startup scientific publications* measures the stock of scientific publications that the startup has published to date. It is an important control, because in biotechnology discoveries are often both published and patented (Murray and Stern, 2006; Stokes, 1997), and therefore today's publications are a strong indicator of tomorrow's patents. This variable was hand-collected from the Web of Knowledge database, matching scientists' declared institution to the name of the startup, as defined in previous work (Agrawal and Henderson, 2002; Azoulay, Ding, and Stuart, 2009; Nelson, 2012).

The variable *Startup age* (in years) is relevant, because some time is required to develop the innovation, but too much time without an innovation signals limited capability to do so. The date of founding was hand-collected using company websites (and the Internet Archive, when necessary) and Factiva news sources.

A set of five dummies account for the specific *Industry segment* within biotechnology: Bio pharmaceuticals, Gene and DNA technology, Bio IT and services, Industrial biotechnology, and Bio instrumentation/engineering. This variable seeks to account for variations in the speed of innovation. The variable was hand-coded by a graduate student in the Master of Biotechnology program at the University of Pennsylvania, by reading and categorizing information on each biotechnology startup's activities from their websites and Factiva news sources.

Finally, the technology bubble's peaking in 2000 and 2001 shook the financing of startups across technology sectors, including biotechnology. Three dummies account for the big trends in the period: *Time before tech bubble (≤ 1999)*, *Time during tech bubble (2000, 2001)*, and *Time after tech bubble (≥ 2002)*.

RESULTS

Descriptive statistics

Table 1 shows the descriptive statistics at the time of first VC investment. Out of 923 startups, 429 (46%) had a patent at the time of first VC investment. Of the 494 startups that did not, 240 (49%) applied for a patent during the study's window of observation, in 692 days on average. *VC life-sciences specialization* is relatively high, on average 0.56, which is not surprising given that life sciences is a complex field; yet there is significant variation, with a standard deviation of 0.35. Importantly, *VC industry specialization* is economically comparable across levels of *Country life-sciences patent stock*: at 52 percent (58%) when *Country life-sciences patent stock* is weak (strong). Table 2 presents correlations. *VC life-sciences specialization* is uncorrelated with *VC experience* (0.02, p-value=0.494). Not surprisingly, it is correlated with *Startup Capital* (0.16, p-value=0.000) and with younger firms (correlation with *Startup age* at -0.11, p-value=0.001).

~ INSERT TABLES 1 AND 2 ABOUT HERE ~

Estimating the time to first patent

Table 3 estimates a Cox regression model on *Time to first patent after VC investment*. Model 1 estimates the controls only. As expected, *Startup capital* increases the hazard of first patent. Model 2 adds the main independent variable. *VC life-sciences specialization* has a positive and significant (p-value=0.030) effect on the hazard of patenting, supporting Hypothesis 1. Models 3, 4, and 5 test the effect for weak, moderate, and strong levels of *Country life-sciences patent stock*, respectively. As predicted, the effect of *VC life-sciences specialization* is statistically significant only for moderate levels of *Country life-sciences patent stock*, supporting Hypothesis 2.

~ INSERT TABLE 3 ABOUT HERE ~

Figure 1 shows the hazard curve for three levels of *VC life-sciences specialization* (at mean, and +/– a standard deviation). The hazard of applying for the first patent peaks between 1 and 2 years after investment by the first VC and declines afterwards. Therefore, there is a window of opportunity in which the first patent is more likely to happen. This is also the period when the effect of *VC life-sciences specialization* is greater. The cumulative hazard is shown in Figure 2. Figure 3 shows the hazard curve for the three levels of *Country life-sciences patent stock*, showing graphically that the effect of *VC life-sciences specialization* is significant only for moderate levels of *Country life-sciences patent stock*.

~ FIGURES 1, 2 AND 3 ABOUT HERE ~

Assessing sample selection bias

Table 4 presents the results for the logit model on the variable *Startup first patent before VC investment* on the full sample. Model 1 estimates controls only, finding that greater *Country investment in R&D/GDP* and greater *Country GDP per capita* increase the likelihood of having a patent. Interestingly, *Country life-sciences patent stock* reduces the likelihood of having a patent at first VC investment, which may imply that patents are less important as a signal when the research environment is stronger. *Startup scientific publications* and *Startup age* both increase the chances that the startup will have a patent. Model 2 adds the main independent variable. The coefficient for *VC life-sciences specialization* is not significant (p-value=0.480). Models 3, 4, and 5 repeat Model 2 for the three levels of *Country life-sciences patent stock* (weak, moderate, and strong, respectively). For moderate levels (Model 4), *VC life-sciences specialization* is not significant (p-value=0.560). Interestingly, for strong levels (Model 3), *VC life-sciences specialization* is negative and significant (p-value=0.049), and hence specialist VC firms choose startups with no patents. Overall, I find no evidence of sample selection bias: a higher level of

VC specialization is not associated with the selection of startups with a patent. This does not mean that selection is not possible, because specialist VC firms may be selecting on unobservable variables, but it suggests that selection is not the main driver of the effect.

~ INSERT TABLE 4 ABOUT HERE ~

Economic significance

The impact of VC specialization on the time to first patent is economically significant. In Table 3, Model 2, the hazard ratio for the full range of VC specialization is 1.55. Consider two startups, Alpha and Beta, equal except for their investors: Alpha is backed by a specialist VC (VC specialization = mean + sd = 0.9) and Beta by a generalist with biotech experience (VC specialization = mean – sd = 0.2). Alpha is at a 40 percent increased hazard of patenting with respect to Beta. This effect is greater when *Country life-sciences patent stock* is moderate. On Model 4, the hazard ratio is 2.25: when Alpha and Beta are located in a country with a moderate country research environment, Alpha is at a 90 percent increased hazard of patenting with respect to Beta.

Figure 4 plots the cumulative hazard for the three levels of strength of *Country life-sciences patent stock* and provides a visualization of the economic impact. Consider again the startups Alpha (backed by a specialist VC firm) and Beta (backed by a generalist) in a moderate-level country research environment (middle graph). Two years after the VC invests (as marked by the dotted blue line), Beta is at a 20 percent cumulative hazard of patenting. This is roughly the same as an average startup in a country with a weak research environment (top graph). Alpha is at roughly a 40 percent cumulative hazard of patenting, which is roughly the same as an average startup in a country with a strong research environment (bottom graph). Essentially, a specialist VC firm can level Alpha with an average startup in the strong scenario, and a generalist VC firm can level Beta with an average startup in the weak scenario.

~ INSERT FIGURE 4 ABOUT HERE ~

Robustness

The results are robust to a variety of different specifications. First, the results are robust to different models: for Cox models, lognormal and log-logistic—both with hazard functions consistent with the fitted hazard function; and for selection, a probit instead of a logit. Second, the results are robust to excluding U.S. startups. Third, the results are robust to measuring the strength of country research environment using the *Country investment in R&D/GDP*. Fourth, the results are robust to dropping some controls (specifically *VC experience* and *Startup scientific publications*), to limiting the startup age to seven years, to including year fixed-effects instead of periods, and to controlling for corporate VC investments. Finally, the results are robust to controlling for the change in the American Inventor's Protection Act of 1999, by which patent applications are made public.

UNCOVERING THE MECHANISMS

Up to this point, I have argued and showed that there is an economically significant effect of VC specialization on the speed of startup innovation, an effect that could be driven by selection or by treatment. In what follows, I leverage the qualitative data from the interviews to shed light on these mechanisms. First, I discuss qualitative evidence that suggests that specialist VC firms may not always select the most promising startups. Then, I discuss how specifically specialist VC firms may help startups innovate faster (i.e., treatment). The interviews reveal two specific problems that startups face in their innovative process and that specialist VC firms can help them address: the *value translation problem*, or how to translate the science into an innovation that has the potential to generate revenue, and the *regulatory problem*, or how to structure the innovation process from the start so that all scientific tests can be used in the drug development process.

Selecting fixer-uppers

Selecting the most promising startup can be expensive, because the competition of several interested investors drives up the valuation. With a higher price at investment, the return on investment goes down. An interviewee at a specialist VC firm explains that he selects startups that are not great:

> *We now have a new asset, one we have created, that has a lot of potential. But it is not competitive. Because the initial idea was objectively not so good, and other investors also realized this, then the price doesn't go up. And it is not that other investors don't realize that small molecule was not the way to go and other modalities may have more future. But they are asset managers, they are not asset shapers. But we are [asset shapers], so we can benefit from that. That doesn't mean that we are not willing to invest in an idea that is just right on all dimensions, and about 20 percent of our investments are like that. But the other 80 percent we shape, and overall this means that we drive the [average investment] price down.* (Interview with a specialist VC).

This quote is important for two reasons. First, it shows that selection and treatment can go hand in hand. This VC firm selects a startup because it can treat it and help it succeed, just as we might buy a fixer-upper house with problems we can address. In essence, specialist VC firms, at least in the early stages, may not always select the most promising startups. Second, just as a fixer-upper home is cheaper but once fixed recovers its full value, a startup that is "objectively not so good" (as the quote says) is cheaper as well, but with the fixes it recovers its full value. The rate of return on that investment is therefore higher.

Previous research has generally assumed that VC firms always seek to select the most promising startups (e.g., Baum and Silverman, 2004; Sørensen, 2007). While this is probably true in many cases, the most promising startups could be more expensive—with exceptions (Hsu, 2004). The quote above shows that selection can work in a different way, one that is intrinsically related to treatment and that considers the valuation of the firm. While this is only one case, I believe it is a relevant one, in the spirit of Siggelkow's talking pig (Siggelkow, 2007).

Helping the startup solve the value translation problem

If specialist VC firms can help startups innovate, then we need to understand what problems the VC can help the startup solve. The first problem startups face is defining their innovation in a way that has value for the customer and can be commercialized. I coin the term *value translation problem*, defined as the "problem of understanding how the innovation will create value for the customer and how that value will be appropriated by the startup." This term closely mirrors the industry-defined science translation problem, which is the challenge of transforming basic science, often at the university, into applied science that can be patented and eventually become a product.[6] However, my interviews suggest that beyond science translation, startups also face the problem of developing a product that can be commercialized and therefore must understand what that commercialization will entail. For instance, once a drug is developed for a particular disease, they need to know what other drugs are prescribed for that disease and whether healthcare insurance will pay for that new drug. In my interviews, venture capitalists explained what this value translation problem entails:

> *The challenge for scientists is that they often don't think about the commercial application of the science. You need to make the two ends meet: the basic science, and the indication and clinical trials they need to run. The way you want to do this is to know where you start and where you should end, and then you figure out how to get there. But scientists don't always do this. The amount of business plans we see where the science is terrific, but they have not even thought about the indication!* (Interview with a specialist venture capitalist)

Specialist VC firms have the people and understanding of the innovation process—from science, to patent, and then to drug development—to help startups overcome this problem. Indeed, this mechanism is consistent with the findings of Samila and Sorenson (2010) that VC

[6] The National Center for Advancing Translational Sciences (NCATS) defines translation as "the process of turning observations in the laboratory, clinic and community into interventions that improve the health of individuals and the public—from diagnostics and therapeutics to medical procedures and behavioral changes" (NCATS, 2019)

firms catalyze the transition from academic science to patent. The specific help VC firms can provide depends on the extent to which they are specialized and on the specific capabilities they have developed. A generalist does not have the capabilities to help with the innovation process, as another venture capitalist explains:

> *We are not involved in R&D. We just don't have the capabilities. We help with legal, contracts, marketing and sales, hiring, but we don't do R&D. That part is up to them.* (Interview with a generalist venture capitalist)

In contrast, a specialist VC firm can leverage its industry contacts to connect the startup to experts that can help the startup understand the business side of the innovation, as a venture capitalist explained:

> *The scientists know about the science but they don't know about the pharmaceutical business. One thing I have done is that I have contacts from my portfolio firms, and I have brought this founder of another firm, with 20 years of experience on pharma, to just spend a couple of days at this startup to help them understand the pharmaceutical aspect. We also organize workshops of a day or a half day, where we bring all the startups in life sciences, and we bring experts to discuss IP law, or online marketing, or how to create a website.* (Interview with a specialist venture capitalist)

A specialist VC firm also has the capabilities to be more directly involved in the innovative process and to provide direct advice on the direction the innovation should follow from the start in order to create a product with more value. The quote below provides an example of very active involvement in the startup to solve the value translation problem:

> *We pivot the idea in three dimensions. First, the modality: for instance, say that the entrepreneur is a chemist and he has come up with a small molecule, because that is what he does as a chemist . . . We may like the general idea, but see more future in a different modality, say, immunotherapy. Then we have pivoted the modality. Second is the target disease: say the startup wanted to apply to it Alzheimer's. But Alzheimer's is a very difficult disease to tackle. However, it may as well apply to Parkinson's, so we pivot and target that instead. Third, the person: now that we have pivoted the modality and the disease, we may need another person to do this, not the original chemist.* (Interview with a specialist venture capitalist)

The value translation problem is not one to be solved with a marketing gimmick, but one that is better addressed from the start of the innovation process, because choices that can be made early will condition the extent to which commercialization will be possible. The previous quote shows this is the case, because the venture capitalist describes changing decisions that are made early in the process (e.g., the modality of the research, the target disease, and the research team). These decisions take the innovation process down a path that is difficult to reverse but that can have important implications for the value of the final product. Another example that highlights the importance of acting early comes from the quote below, where the venture capitalist explains how her firm follows startups from the very beginning—well before this VC firm can invest in them—and gives them free advice so that, when the startup is at the stage when the VC firm can invest, the startup has made the right decisions in their innovative process:

> *We invest in firms we have been following for a while. When there is a new firm in the sector, we generally invite them for an introductory meeting. We find out about their plans and we give them advice for free, even put them in contact with experts as needed, with incubators, etc. Then we follow them, their milestones, and if they progress in two or three years, we invest in them.* (Interview with a specialist venture capitalist)

Helping the startup solve the regulatory problem

The second problem biotech startups face is the *regulatory problem*: after they patent, they need to go through the drug development process at the FDA (in the US) or the EMA (in the EU) in order to get their drug approved. This process requires providing scientific evidence of safety and effectiveness, typically through three phases of clinical trials. Startups that are going through this process for the first time do not have the information to anticipate what is required to prove an effect to the regulator, and the scientific standards required sometimes differ from those in academic publications. A venture capitalist explains what this problem entails:

> *We help them set procedures in place from day one. Because when a company starts preclinical trials on mice, they do their best, but they do it their way, coming from academia. But later on in the [drug development] process the regulator will want to see things done in a certain way, there are quality controls they need to do, there is certain documentation processes that will allow them to have what they need when it is time to apply to the regulator. And these processes are cumbersome for the startup at first, but in the end they save time and make the process smoother.* (Interview with a specialist venture capitalist)

The regulatory problem has been studied before in a similar setting. Alvarez-Garrido and Dushnitsky (2016) found that corporate VC firms foster startup innovation by providing regulatory advice to startups. In this paper, I argue that specialist VC firms have the people and the contacts required to identify the problems early on in the innovation process and to advise on the specific documentation processes or standards of proof, so that the scientific tests conducted early on are valid later on in the drug development process. The venture capitalist above "helps them set procedures in place from day one." In the quote below, another venture capitalist explains how they identify the regulatory problem and provide advice directly or put startups in touch with experts that can provide advice:

> *We have been in business for over 10 years, and we know better than the startup when they are going to have a regulatory problem. Sometimes they have a really cool technology, but we know it is not going to work well on the workflow of the physician, or the technology is such that there will be a regulatory hurdle they don't suspect, or there is simply an issue of the economics not making sense, the technology cannot be commercialized. We cannot fix these problems for them. What we do is give them advice, explain what the problem is and what the solution might be, we put them in contact with regulatory experts if needed, or give them advice based on our experience, we can put them in contact with sites to get the clinical trials done.* (Interview with a specialist venture capitalist)

Three mechanisms at play

In conclusion, qualitative evidence from the interviews suggests that at least three mechanisms are jointly at play—one that involves selection and two that involve treatment. First, specialist VC firms carefully select the startups they invest in. But while previous literature suggests that they always select the most promising, my interviews suggest that in some cases they may select fixer-uppers, startups that are not promising now but could be if the specialist VC helps them. Second, specialist VC firms help the startup translate the value of the innovation, so that they can fully realize its potential. This is not just a marketing gimmick, but an early-stage intervention to help the scientists define what the technological innovation should entail. Third, specialist VC firms help the startup with the regulatory process from the start, by providing advice on the steps the innovation process should follow from the outset to facilitate the regulatory process. To help the startups, specialist VC firms leverage the research environment when needed, connecting the startup to regulatory and industry experts, as well as to other startups. This point provides further insight into the mechanisms underlying hypothesis 2 and into the importance of the country research environment as a moderator of the effect.

DISCUSSION AND CONCLUSION

This paper has sought to uncover the impact of VC firms on startup innovation by leveraging the heterogeneity in the VC firm strategy as well as the heterogeneity in the research environment of the country in which the startup innovates. I find that startups backed by specialist VC firms patent faster than those backed by generalist VC firms. I also find that the strength of the country research environment is both a substitute and a complement, and therefore the effect of VC specialization is significant when the research environment is moderate. The effects are economically important: on average, startups patent 40 percent faster when backed by a specialist VC firm *versus* an experienced generalist; if the research environment is moderate, then 90 percent faster.

To gain a richer understanding of the mechanisms that drive this effect, I leverage qualitative data from 18 interviews with VC partners. I have shown that specialist VC firms do not select firms that have patents, an important signal of quality (Hsu and Ziedonis, 2013); while this reduces concerns with selection, however, it is possible that they may still be selecting on unobservable variables. Qualitative data suggests that, at least in some cases, specialist VC firms do not select the most promising startups, but those that could be promising yet need help to achieve their potential.

It is difficult to identify what specific mechanisms drive the treatment effect quantitatively, since they work in the same direction. Qualitative data suggests that specialist VC firms helps startups overcome two specific problems that they face in their innovative process: the *value translation problem*, or how to translate the science into an innovation that has the potential to generate revenue, and the *regulatory problem*, or how to structure the innovation process from the start so that all scientific tests can be used in the drug development process. In both mechanisms, specialist VC firms leverage external resources from the research environment.

Further research will be needed to gain a deeper understanding of the specific mechanisms at play. More research is required to understand specifically the mechanisms of selection *versus* treatment. We generally assume that investors will, when possible, select the most promising startups. Yet my interviews suggest that we should also consider the valuation of the startups. More research is also needed to further understand the advantages of a generalist strategy. Generalist VC firms typically contribute to startup performance through helping manage the firm, and it is an open question whether they do a better job than specialists in this regard. Additional research is needed to identify the specific mechanisms (i.e., helping with the value translation problem, or helping with the regulatory problem) that underlie the effect. This effect could be unpacked by studying the specific team the venture capital firm has, including their degrees or prior experience, in the spirit of the research by Bottazzi *et al.* (2008). It is possible that startups whose founding teams are all scientists may benefit more from the help that VC firms provide. Finally, more research is needed to assess to what extent the findings are generalizable to other industries, possibly science-based, such as artificial intelligence.

This paper has sought to contribute to the entrepreneurship literature by shedding light on the mechanisms by which VC firms contribute to startup innovation. Previous research had demonstrated the contribution of VC firms to startup innovation, albeit at industry and regional levels (Kortum and Lerner, 2000; Samila and Sorenson, 2010), and had studied how different investor classes contributed to startup innovation (Alvarez-Garrido and Dushnitsky, 2013, 2016; Cox-Pahnke *et al.*, 2015). This paper contributes more generally to a broader stream of literature that defines the specific contribution of VC firms to the performance of startups (e.g., Alvarez-Garrido and Guler, 2018; Gorman and Sahlman, 1989; Hellmann and Puri, 2002; Hsu, 2006).

This paper has sought to contribute to practice by showing how specialist VC firms contribute to startup innovation. This is important for policy makers. The VC model has been nurtured by governments all over the world precisely to foster innovation, and in turn economic development. The results of this paper show that specialist VC firms can help, but that certain strength the country research environment is necessary. The results can also inform startups that are searching for potential investors, as the results can help the startups understand which VC firm and in which context may, on average, be better positioned to help them overcome obstacles to their innovation process. And finally, these findings are also relevant for VC firms. VC firms make a strategic choice when they specialize, one that has trade-offs, but they lack the data to evaluate whether the choice was correct. This paper helps them assess the impact regarding an important metric—startup innovation. In an interview, a specialist VC partner asked me "whether specialist *versus* generalist funds make a difference on the value added to a firm." I could not answer his question then, but he inspired me to find the answer that this paper has sought to provide.

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Table 1. Descriptive statistics, at time of first VC investment

	Country life-sciences patent stock:	All		Weak		Moderate		Strong	
	Variable	**Mean**	**s.d.**	**Mean**	**s.d.**	**Mean**	**s.d.**	**Mean**	**s.d.**
1	Startup first patent before VC investment	0.46	0.50	0.45	0.50	0.45	0.50	0.49	0.50
2	Startup first patent after VC investment[a]	0.49	0.50	0.42	0.50	0.48	0.50	0.55	0.50
3	Time to first patent after VC investment (days)[a]	1,296.34	907.20	1282.13	830.48	1,582.22	1,088.77	1,039.22	687.65
4	VC life-sciences specialization	0.56	0.35	0.52	0.33	0.57	0.34	0.58	0.37
5	VC experience[b]	88.15	148.01	68.04	133.02	106.35	188.45	89.98	115.17
6	Country life-sciences patent stock[c]	5,401.21	4,868.11	293.18	222.78	4,725.01	4,274.45	10,473.59	358.23
7	Country investment in R&D/GDP	2.47	0.50	2.33	0.80	2.41	0.29	2.65	0.06
8	Country GDP per capita ($10k)	2.90	0.73	2.26	0.72	2.80	0.47	3.55	0.08
9	Startup capital ($100k)	0.31	0.84	0.20	0.81	0.23	0.49	0.48	1.05
10	Startup scientific publications	2.28	10.09	1.73	6.22	1.61	4.69	3.33	15.02
11	Startup age	2.15	2.49	2.35	2.59	1.85	2.12	2.25	2.67
12	Industry segment: Bio pharmaceuticals	0.45	0.50	0.36	0.48	0.46	0.50	0.51	0.50
13	Industry segment: Gene and DNA technology	0.21	0.41	0.23	0.42	0.21	0.40	0.21	0.40
14	Industry segment: Bio IT and services	0.16	0.37	0.15	0.36	0.15	0.35	0.17	0.38
15	Industry segment: Industrial biotechnology	0.08	0.27	0.12	0.32	0.08	0.28	0.04	0.19
16	Industry segment: Bio instrumentation/engineering	0.11	0.31	0.14	0.35	0.11	0.31	0.07	0.26
17	Time before tech bubble (≤1999)	0.29	0.45	0.31	0.46	0.51	0.50	0.08	0.27
18	Time during tech bubble (2000, 2001)	0.35	0.48	0.30	0.46	0.34	0.47	0.41	0.49
19	Time after tech bubble (≥2002)	0.36	0.48	0.39	0.49	0.15	0.36	0.51	0.50
	Number of startups, full sample	923		295		292		336	
	Number of startups, no patents when VC invests	494		163		161		170	

[a] Conditional on *Startup first patent before VC investment* = 0
[b] Descriptive statistics shown for 1 investment. All models shown for 100 investments
[c] Descriptive statistics shown for 1 patent. All models shown for 100 patents

Table 2. Correlations, at time of first VC investment

	Variable	1	2	3	4	5	6	7	8	9
1	Startup first patent before VC investment									
2	Startup first patent after VC investment	NA[a]								
3	Time to first patent after VC investment	NA[a]	-0.65							
4	VC life-sciences specialization	-0.03	0.15	-0.12						
5	VC experience	0.05	0.13	-0.03	0.02					
6	Country life-sciences patent stock	0.06	0.19	-0.12	0.04	0.01				
7	Country investment in R&D/GDP	0.11	0.08	-0.02	0.01	-0.01	0.32			
8	Country GDP per capita	0.13	0.13	-0.17	0.10	0.01	0.80	0.37		
9	Startup capital	0.12	0.12	-0.13	0.16	0.21	0.16	0.13	0.16	
10	Startup scientific publications	0.17	0.00	0.00	-0.01	0.02	0.06	0.01	0.07	0.11
11	Startup age	0.32	-0.18	0.07	-0.11	-0.03	-0.04	0.03	0.03	0.07
12	Industry segment: Bio pharmaceuticals	-0.02	0.03	-0.05	0.15	0.05	0.10	0.01	0.11	0.07
13	Industry segment: Gene and DNA technology	0.01	0.08	-0.02	-0.01	0.04	-0.02	-0.02	-0.04	0.02
14	Industry segment: Bio IT and services	-0.01	-0.07	0.02	-0.05	-0.01	0.04	-0.05	0.03	-0.01
15	Industry segment: Industrial biotechnology	-0.02	-0.02	0.06	-0.13	-0.08	-0.11	0.01	-0.11	-0.05
16	Industry segment: Bio instrumentation/engineering	0.04	-0.06	0.03	-0.05	-0.06	-0.09	0.06	-0.06	-0.08
17	Time before tech bubble (≤1999)	0.00	0.25	0.15	0.02	-0.01	0.03	-0.12	-0.09	-0.07
18	Time during tech bubble (2000, 2001)	-0.01	0.08	0.07	-0.04	0.06	-0.08	0.15	-0.10	0.06
19	Time after tech bubble (≥2002)	0.01	-0.32	-0.22	0.02	-0.05	0.05	-0.03	0.18	0.00

	Variable	10	11	12	13	14	15	16	17	18
11	Startup age	0.32								
12	Industry segment: Bio pharmaceuticals	0.04	-0.06							
13	Industry segment: Gene and DNA technology	0.00	-0.04	-0.47						
14	Industry segment: Bio IT and services	0.01	0.04	-0.39	-0.23					
15	Industry segment: Industrial biotechnology	-0.03	0.10	-0.26	-0.15	-0.13				
16	Industry segment: Bio instrumentation/engineering	-0.05	0.02	-0.31	-0.18	-0.15	-0.10			
17	Time before tech bubble (≤1999)	-0.05	-0.15	0.01	0.00	0.00	-0.01	-0.02		
18	Time during tech bubble (2000, 2001)	0.00	-0.05	-0.08	0.11	-0.02	0.01	0.00	-0.47	
19	Time after tech bubble (≥2002)	0.05	0.20	0.08	-0.11	0.01	0.00	0.02	-0.48	-0.55

All correlations 0.07 or greater are significant at $p < 0.05$

All correlations calculated with 923 observations, except for columns 2 and 3 with 494 observations

[a] Because *Startup first patent after VC investment* and *Time to first patent after VC investment* are conditional on *Startup first patent before VC investment* = 0, correlation is not defined

Table 3. Time to first patent after VC investment, conditional on no patents at time of investment

Country life-sciences patent stock **Model: Cox**	**All** **(1)**	**All** **(2)**	**Weak** **(3)**	**Moderate** **(4)**	**Strong** **(5)**
VC life-sciences specialization		0.439 [0.030]	-0.024 [0.955]	0.814 [0.038]	0.356 [0.298]
		(0.202)	(0.424)	(0.392)	(0.343)
VC experience	0.046 [0.295]	0.050 [0.257]	0.021 [0.856]	0.024 [0.736]	0.151 [0.127]
	(0.044)	(0.044)	(0.113)	(0.071)	(0.099)
Country life-sciences patent stock	0.003 [0.273]	0.003 [0.224]	0.110 [0.068]	-0.008 [0.227]	-0.100 [0.473]
	(0.002)	(0.002)	(0.060)	(0.007)	(0.139)
Country investment in R&D/GDP	-0.249 [0.253]	-0.245 [0.269]	-0.311 [0.211]	0.387 [0.582]	-17.229 [0.198]
	(0.218)	(0.222)	(0.248)	(0.702)	(13.376)
Country GDP per capita	0.249 [0.132]	0.223 [0.179]	0.042 [0.836]	0.997 [0.058]	-15.202 [0.172]
	(0.166)	(0.166)	(0.201)	(0.525)	(11.125)
Startup capital	0.301 [0.001]	0.266 [0.007]	0.625 [0.252]	0.088 [0.818]	0.343 [0.007]
	(0.093)	(0.099)	(0.545)	(0.382)	(0.128)
Startup scientific publications	-0.008 [0.820]	-0.008 [0.813]	0.007 [0.863]	0.122 [0.111]	-0.174 [0.035]
	(0.034)	(0.034)	(0.039)	(0.076)	(0.082)
Startup age	-0.097 [0.042]	-0.086 [0.074]	-0.042 [0.499]	-0.276 [0.045]	-0.063 [0.460]
	(0.048)	(0.048)	(0.062)	(0.137)	(0.086)
Time before tech bubble (≤1999)	0.250 [0.099]	0.256 [0.091]	0.251 [0.405]	0.575 [0.201]	-3.645 [0.124]
	(0.151)	(0.152)	(0.301)	(0.450)	(2.369)
Time after tech bubble (≥2002)	-0.709 [0.000]	-0.725 [0.000]	-1.404 [0.002]	-0.924 [0.117]	-1.474 [0.181]
	(0.190)	(0.190)	(0.448)	(0.590)	(1.102)
Observations	494	494	163	161	170
Industry segment F.E., included	Yes	Yes	Yes	Yes	Yes
Industry segment F.E., joint LR test	16.03 [0.025]	12.12 [0.097]	9.29 [0.233]	5.47 [0.602]	15.91 [0.026]
LR chi^2	69.82 [0.000]	74.59 [0.000]	46.80 [0.000]	37.03 [0.001]	30.93 [0.006]
Log-Likelihood	-1339.0	0.439 [0.030]	-299.0	-343.7	-419.5

Standard error in parentheses, p-values in block brackets

Table 4. Selection: Likelihood of the startup having its first patent at time of VC investment

Country life-sciences patent stock **Model: Logit**	**All** **(1)**	**All** **(2)**	**Weak** **(3)**	**Moderate** **(4)**	**Strong** **(5)**
VC life-sciences specialization		-0.153 [0.480]	-0.174 [0.703]	0.237 [0.560]	-0.708 [0.049]
		(0.216)	(0.457)	(0.407)	(0.360)
VC experience	0.047 [0.374]	0.045 [0.390]	0.028 [0.815]	0.060 [0.420]	0.087 [0.485]
	(0.052)	(0.052)	(0.120)	(0.075)	(0.125)
Country life-sciences patent stock	-0.005 [0.043]	-0.005 [0.038]	0.019 [0.771]	0.013 [0.170]	-0.110 [0.513]
	(0.003)	(0.003)	(0.065)	(0.010)	(0.168)
Country investment in R&D/GDP	0.291 [0.069]	0.288 [0.072]	0.368 [0.042]	-1.464 [0.014]	8.434 [0.557]
	(0.160)	(0.160)	(0.180)	(0.593)	(14.374)
Country GDP per capita	0.686 [0.000]	0.698 [0.000]	0.662 [0.002]	0.349 [0.596]	-5.243 [0.710]
	(0.190)	(0.191)	(0.214)	(0.658)	(14.124)
Startup capital	0.145 [0.215]	0.160 [0.186]	1.164 [0.042]	0.404 [0.332]	0.068 [0.621]
	(0.117)	(0.121)	(0.572)	(0.416)	(0.137)
Startup scientific publications	0.120 [0.000]	0.120 [0.000]	0.107 [0.027]	0.089 [0.093]	0.098 [0.057]
	(0.030)	(0.030)	(0.048)	(0.053)	(0.052)
Startup age	0.282 [0.000]	0.279 [0.000]	0.184 [0.001]	0.352 [0.000]	0.385 [0.000]
	(0.039)	(0.039)	(0.058)	(0.081)	(0.074)
Time before tech bubble (≤1999)	0.249 [0.178]	0.253 [0.171]	0.297 [0.436]	-0.406 [0.458]	-0.331 [0.911]
	(0.185)	(0.185)	(0.381)	(0.548)	(2.964)
Time after tech bubble (≥2002)	-0.272 [0.140]	-0.269 [0.145]	-0.136 [0.699]	-0.390 [0.390]	0.717 [0.514]
	(0.184)	(0.184)	(0.353)	(0.454)	(1.098)
Constant	-3.432 [0.000]	-3.356 [0.000]	-3.299 [0.000]	0.928 [0.650]	6.653 [0.943]
	(0.582)	(0.591)	(0.739)	(2.048)	(93.404) [0.943]
Observations	923	923	295	292	336
Industry segment F.E., included	Yes	Yes	Yes	Yes	Yes
Industry segment F.E., joint LR test	143.000 [0.000]	141.160 [0.000]	38.840 [0.000]	47.560 [0.000]	79.860 [0.000]
Pseudo-R^2	0.135	0.136	0.174	0.152	0.191
Log-Likelihood	-551.2	-551.0	-167.5	-170.4	-188.5

Standard error in parentheses, p-values in block brackets

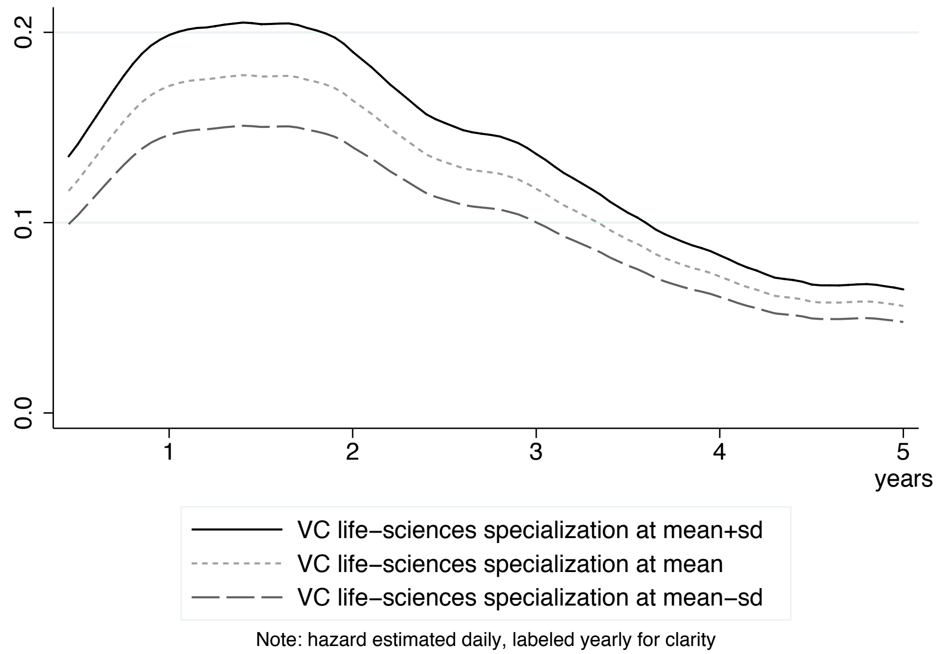

Figure 1. Hazard, by VC life-sciences specialization

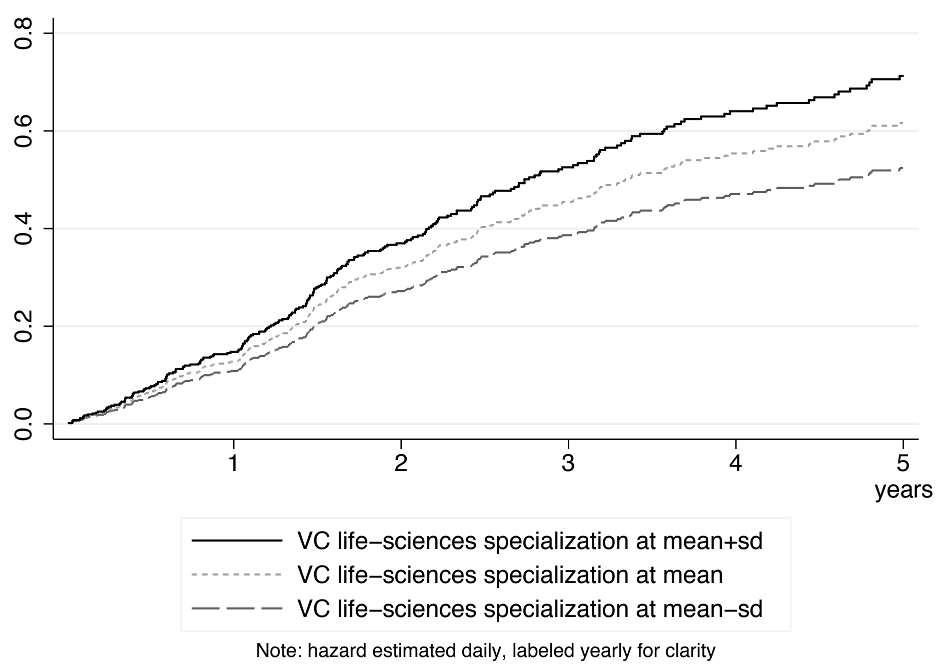

Figure 2. Cumulative hazard, by VC life-sciences specialization

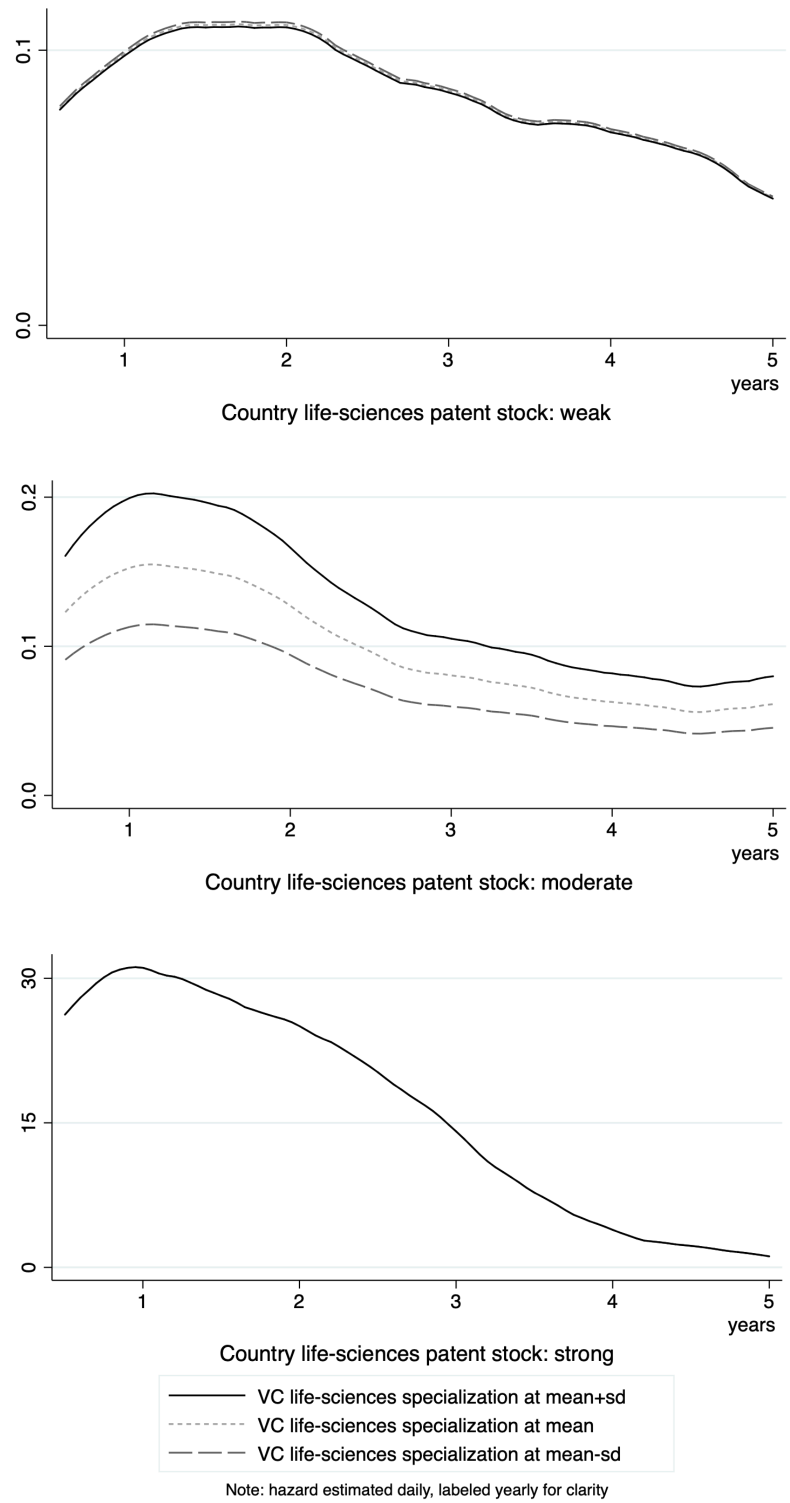

Figure 3. Hazard, by country life-sciences patent stock and by VC life-sciences specialization

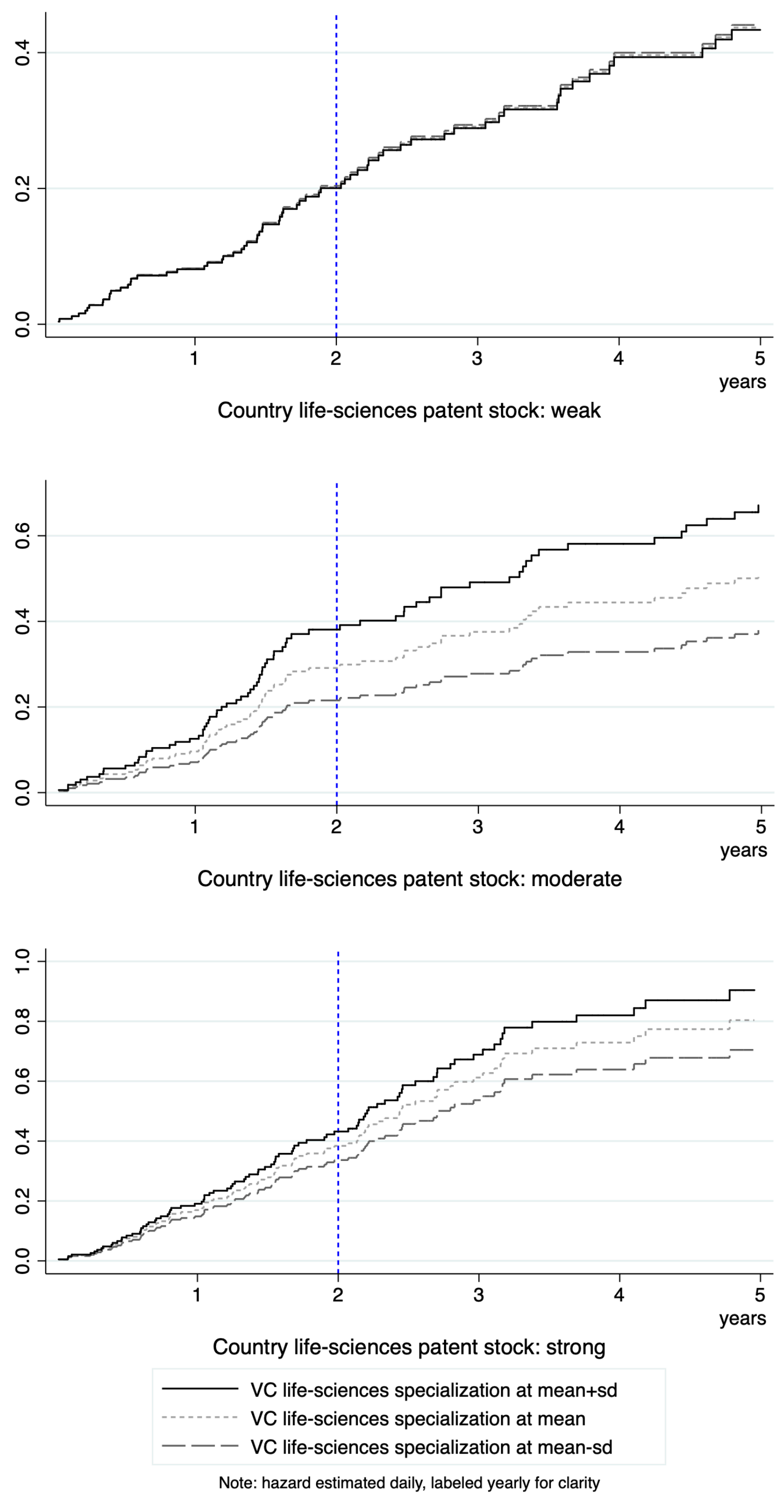

Figure 4. Cumulative hazard, by country life-sciences patent stock and by VC life-sciences specialization