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Abstract

Venture capital has emerged as an integral component within the entrepreneurial ecosystem. This dissertation seeks to understand how venture capital has influenced entrepreneurial activities in three different contexts concerning various sources of risk capital. The first study investigates how startups adjust their technological positioning after securing corporate venture capital, delineating a nuanced framework based on an interplay of learning synergies and competitive threats. The theory is tested in the mature context of European and North American IT industry and finds that startups' technological positions tend to converge, diverge, or maintain distance from their corporate investors' parent corporations, depending on the initial technological distance prior to receiving investments. The second study shifts its focus toward an emerging industry and explores the impact of venture capital on both industry dynamics and startups' product positioning. The chapter relies on a uniquely compiled panel dataset of startups entering the nascent plant-based food and beverage industry, as well as their historical website data tracing the evolution of product framing within the industry. The empirical patterns reveal that venture capital interests elicit entry during the initial stage of industry emergence. However, a contrasting deterring effect is observed, when venture capital deals flow to existing portfolio companies through follow-on investments. Furthermore, venture capital supports startups in broadening the market appeal of the nascent niche market by navigating the complex institutional environment and strategically combining multiple institutional logics for product framing. The final study delves into the growing trend of investing in sustainability, and sets out to trace the influence originating from the source of venture capital. The chapter examines how limited partners with varying preferences for social impact wield their influence on shaping venture capital funds' sustainability orientation. Findings from a large sample of venture capital funds and their investment history indicate that funds predominantly backed by limited partners with a higher willingness to pay for social impact include a greater number of sustainability-driven startups in their portfolio. Further, this effect is more pronounced in conventional funds (as opposed to impact funds); in funds located in countries with weak (instead of strong) norms toward sustainability performance; and in funds managed by first-time and young GPs. Through these studies, this dissertation aims to deepen our understanding of the multifaceted impact of venture capital.

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Chapter 1 Introduction

Venture capital (VC) plays a pivotal role in the modern entrepreneurial ecosystem. As of 2021, the seven largest U.S. companies by market capitalization, including Apple, Microsoft, Amazon, received most of their early-stage external funding from VCs (Gornall & Strebulaev, 2022). Moreover, VC-backed companies constituted 41% of the overall market capitalization and were responsible for 62% of the R&D expenditures of public companies in the United States (Gornall & Strebulaev, 2021). Research suggests that the positive effect goes beyond companies that are funded by VC (Puri & Zarutskie, 2012), as VC propels emergence and growth of innovative industries (Nanda, Younge, & Fleming, 2015), generate new business establishments (Mollica & Zingales, 2007; Samila & Sorenson, 2010, 2011; Popov & Roosenboom, 2013), create jobs and increase income (Puri & Zarutskie, 2012).

There is an ongoing research interest in understanding the ways in which VCs contribute added value to startups. Findings indicate that VCs not only effectively screen startups with high growth potential (e.g., Engel & Keilbach, 2007), but also nurture startups through post-investment activities. Beyond the provision of capital, VC has been found to foster innovation and technology development (e.g., Hsu, 2006; Reuer & Devarakonda, 2017), to elevate the degree of professionalization (Hellmann & Puri, 2002), to speed up the commercialization process (Hellmann & Puri, 2000), and to accelerate sales growth (Grilli & Murtinu, 2014). Moreover, the involvement of venture capitalists serves as a powerful signal, attesting to the quality and growth potential of the startups (Ragozzino & Reuer, 2007).

Despite the large literature that quantifies these contributions from VCs, the understanding of how VCs contribute remains limited and anecdotal (Da Rin & & Penas, 2017;

González-Uribe, 2020). This dissertation aims to contribute to this understanding by empirically studying how venture capital has influenced entrepreneurial activities in three different contexts concerning various sources of risk capital. In the following, I provide a brief overview of the research scope of these studies.

Chapter 2 focuses on the context of corporate venture capital (CVC). In addition to traditional venture capitalists, the landscape of entrepreneurial financing has witnessed the increasing involvement of risk capital from large established corporations. Notably, in 2021, global CVC-backed funding constituted approximately 30% of the total funding received by startups (CBinsights, 2022). This underscores the growing influence of corporation in shaping the funding landscape for emerging businesses. CVCs differ from independent VCs in their expertise and investment objectives. Especially for technology-based industries, both startups and CVC investors enter into the CVC relationship with the primary objective of accessing and leveraging each other's strategic resources and knowledge. In this study, I investigate the dynamics of technological positioning of a startup in terms of its technological distance in relation to its CVC investor. I argue that both learning opportunities and competitive threats arising from CVC investments shape a startup's technological position. Specifically, I propose three different scenarios of technological distance change following CVC investments: when the technological distance between a startup and its CVC investor is low prior to investment, the technological distance tends to increase post-investment, resulting in a diverging development. Conversely, when the pre-investment technological distance is intermediate, the post-investment technological distance tends to decrease, indicating a converging development. However, when the pre-investment technological distance is high, the technological position remains distant post-investment. I test these predictions by contrasting the patenting histories of 797 European and North American startups in the IT industry that received CVC investments between 1995 and 2017 with those of their respective CVC investors. The theoretical framework and findings offer new insights into how both competitive and learning mechanisms impact the technological positioning of startups following CVC investments.

Chapter 3 shifts its focus to a nascent industry. Anecdotal accounts suggest that the emergence and development of industries including semiconductor, IT, and biotechnology has been propelled by the readily available risk capital for new startups in such sectors (Nanda, Younge, & Fleming, 2015). However, empirical evidence on how VC systematically influences dynamics in a nascent industry has been relatively scarce. In this study, I explore how venture capital contributes to shape entrepreneurial entry and market positioning in a nascent industry. I propose that at the initial stage of industry emergence, investors' interests facilitate new entry by signaling market validity and by enhancing the favorability of the opportunity. However, as the nascent market expands, a significant portion of available capital tends to be directed towards follow-on investments in ventures that received VC funding in previous rounds, thereby deterring entry of new startups. I further propose that ventures are inclined to adopt a broader market positioning following VC investments, leveraging multiple institutional logics within organizational fields and seeking to expand beyond their initial niche market. I test the theory by compiling a unique panel of startups entering the nascent plant-based food and beverage industry. Taking into account the structure of multi-staging and lifecycle of closed-end funds in the VC industry, I introduce a more nuanced framework that outlines how VCs' evolving investment strategies within a nascent industry influence entry pattern. I also advance the understanding of how VCs help startups in attaining superior product market outcomes.

Chapter 4 delves into the growing trend of investing in sustainability, and sets out to trace the influence originating from the source of capital in VC funds. This study examines how limited partners (LP) with varying preferences for social impact wield their influence on shaping venture capital funds' sustainability orientation. Using a large sample covering 4,419 funds and 45,872 ventures, I found that funds predominantly backed by limited partners with a higher willingness to pay for social impact include a greater number of sustainability-driven startups in their portfolio. Moreover, this effect is more pronounced in conventional venture capital funds and early-stage funds, as well as when the fund is managed by first-time and young VC firms. This contributes to the understanding of LP-GP relationship, indicating that while LPs operate as passive investors without direct involvement in GPs' investment decisions, they still wield substantial influence over a fund's sustainability orientation. This research also empirically demonstrates that institutional investors' preference for sustainability found in other asset classes extends to the market of private equity by supporting more sustainability-driven ventures.

Overall, these three studies aim to deepen our understanding of the multifaceted impact of risk capital on venture outcomes.

Chapter 2 Corporate Venture Capital and Startups' Technological Positioning

2.1 Introduction

Corporate Venture Capital (CVC), a minority equity investment by an established corporation in an entrepreneurial startup (Dushnitsky, 2012), has become an important and prevalent source of funding for startups. In 2021, Global CVC-backed funding accounted for approximately 30% of the total funding received by startups (CBinsights, 2022).[1] While considerable research has documented how receiving CVC investments impacts startups' novelty (Balachandran, 2019; Corredoira & Di Lorenzo, 2019; Polidoro & Yang, 2021), as well as rate of innovation (Alvarez-Garrido & Dushnitsky, 2016; Chemmanur, Loutskina, & Tian, 2014; Pahnke, Katila, & Eisenhardt, 2015; Park & Steensma, 2013), less attention has been given to the question of how a CVC-backed startup adjusts its technological position in relation to its CVC investor, considering that the majority of these investors are often established incumbents within the same industry where the young startup operates. Understanding the dynamics of a startup's technological position is crucial, as it not only lies at the core of the startup's growth and survival but also has significant implications for the technological race and competitive dynamics in the future (Chen, Qian, & Narayanan, 2017). After receiving CVC investments, do startups focus their innovative activities in technological fields that are closely aligned with their CVC investors or venture into distant domains?

To address this question, we build upon existing approaches to the dynamics of technological position and its implications, which have been focused on interfirm relations

[1] From 2016 to 2020, the volume of CVC-backed funding and the number of active corporate investors represent a 122% and 68% increase respectively. In 2020, eight out of the top ten most active corporate investors are large technology firms, such as Google, Microsoft, or Intel.

such as strategic alliances (Mowery, Oxley, & Silverman, 1996, 1998; Stuart & Podolny, 1996), joint ventures (Nakamura, Shaver, & Yeung, 1996), R&D partnerships (Maliatsina & Kimpimäki, 2020), and M&A transactions (Ahuja & Katila, 2001). Similar to geographic location, the difference in technological profile is often conceptualized as the *distance* between the technological positions occupied by a pair of firms in the technological landscape (Jaffe, 1986). Prior studies found that two main forces act upon the technological distance of the dyad following a relationship formation, which push toward either a converging direction or a diverging direction (Nakamura, Shaver, & Yeung, 1996). First, direct or indirect knowledge exchanges and learning synergies make the technological capabilities and resources of two partner firms more similar or overlapping (Mowery, Oxley, & Silverman, 1996, 1998). Second, competition dynamics and perceived rivalry push the firms to take diverging direction in their technological development (Chen, 1996). In fact, in their study of a sample of the US-Japan joint ventures, Nakamura and colleagues (1996) found that an increased technological similarity between parent companies can accelerate the dissolution of their joint venture.

In this paper, we develop and empirically test a theoretical framework where the direction of the technological distance change depends on the pre-CVC technological positions of the dyad, which, we argue, helps to better capture the nuances of the tradeoff between learning opportunities and competitive threats facilitated by CVC relationships.

In our theoretical framework, the technological positions of startups in relation to their CVC investors *prior to* the CVC deal reflect the intensity of an interplay between learning opportunities and competitive threats, and hence influence in a differential way startups' technological positioning after receiving CVC investments. When the pre-investment technological profiles are highly similar, the competitive concern is heightened, and the learning effect is limited due to a great extent of knowledge overlap. Consequently, the competition mechanism dominates, leading to an increase in technological distance to mitigate competition while seeking greater learning benefits (a diverging development). In cases where the pre-investment technological distance is at an intermediate level, the learning effect is prominent, while a moderate level of competition still exists. The interplay between these forces results in a limited decrease in technological distance (a converging development). On the other hand, when the pre-investment technological profiles are highly dissimilar, both learning and competition effects are weak. As a result, the technological relationship remains distant and unchanged.

To test these predictions, we collected data on European and North American startups in the IT industry that have received CVC investments between 1995 and 2017. The IT industry is an ideal setting because technology-related strategic motive is of primary concern for CVC activities (Dushnitsky, 2012). We combined the Pitchbook dataset, which provides better coverage and more accurate funding information (Retterath & Braun, 2020), with the PATSTAT dataset, to obtain the patenting history of both startups and their CVC investors' corporate parents. We measure change of technological distance by contrasting startups' patents five years prior to and five years after CVC investments in relation to corporations' patents. Using a matched sample design with a Difference-in-Difference approach, we were able to uncover the heterogeneous effect of CVC on the lower, middle and upper parts of technological distance distribution. Our findings suggest that compared to a sample of matched startups, receiving CVC investments increases the technological distance between startups and their investors in the lower parts of the technological distance distribution, supporting the notion of a diverging development. By contrast, in the middle parts of the technological distance distribution, CVC investments decreases post-deal technological distance, consistent with the converging hypothesis. In addition, in the uppermost part of the technological distance distribution, CVC investments do not change post-deal technological distance. Supplementing our analyses, we delve into the performance implications of startups' technology positioning concerning their post-deal innovativeness and exit outcomes. Our findings indicate that startups that align their technological position closely with that of their investors following the deal tend to file more patent applications than those that position themselves further away from their investors. Paradoxically, the latter are more likely to experience a successful exit event within our observation window. We elaborate on these findings in the Discussion section below.

We make several contributions to extant literature. First, despite numerous studies that examine the effect of CVC on startups' innovative performance (Kim & Park, 2017), to the best of our knowledge, this is the first paper that directly analyzes the direction and focus of startups' technological activities after CVC investment. Our emphasis on startups' technological position in relation to their CVC investors pre-CVC formation not only renders support for the potential learning synergies and knowledge transfer facilitated by the investment relationship (e.g., Polidoro & Yang, 2021; Smith & Shah, 2013), but also uncovers potential constrains on learning and strategic dynamics. As we shall discuss in the conclusion, this perspective also allows us to provide a possible explanation for the inconsistent findings found in prior literature concerning the innovative benefits of CVC for startups (e.g., Alvarez-Garrido & Dushnitsky, 2016; Chemmanur et al., 2014; Di Lorenzo & Van de Vrande, 2019; Pahnke et al., 2015; Park & Steensma, 2013). Second, we show that a change of the technological position of a CVC-backed startup has a direct bearing on startups' ability to innovate as well as to achieve successful exits. This further sheds light on startups' strategic decision-making processes and the factors that affect their success in the competitive landscape of the industry. We thus contribute to the research on the determinants of performance of technology startups (e.g., Hsu & Ziedonis, 2013). Finally, we contribute to the literature on the dynamics of technological position and its implications in interfirm relations (Mowery, Oxley, & Silverman, 1996, 1998; Stuart & Podolny, 1996; Nakamura, Shaver, & Yeung, 1996; Maliatsina & Kimpimäki, 2020; Ahuja & Katila, 2001) by analyzing the interplay between learning and competition dynamics (Runge, Schwens, & Schulz, 2021) under three different scenarios. The first scenario depicts a converging development, wherein the startup's technological position moves closer to that of their CVC investor. The second scenario illustrates a diverging development, characterized by the startup's technological position moving farther away from their CVC investor. Additionally, we propose a third scenario where the startup's position remains unchanged after receiving CVC investments. By delineating these different scenarios, our research refines the existing understanding of how CVC influences the technological trajectories of startups.

2.2 Theory and hypotheses

First, we build on extant literature to argue that CVC relationship formation both entails learning opportunities and creates potential competitive threats. We then introduce the notion of technological distance between the startup and the investor and illustrate how it can change as a consequence of CVC relationship formation. Finally, we show how learning opportunities and competitive threats vary as a function of pre-CVC technological positions, and how these considerations help predict the direction of change (convergence vs divergence) of the technological distance post-CVC investment.

2.2.1 Corporate venture capital and learning opportunities

Extant research sheds light on the objectives that drive CVC relationship formation from the perspectives of both startups and incumbents. Startups often choose industry incumbents as their equity partner to leverage the numerous unique and valuable resources they offer. Compared to traditional independent VC, CVC investors are equipped with in-depth industry knowledge and connections, in-house scientists, regulatory knowhow, distribution channels and commercialization expertise (e.g., Alvarez-Garrido & Dushnitsky, 2016; Chemmanur et al., 2014; Park & Steensma, 2012). For established incumbents, CVC activities are considered as their strategy to search externally for knowledge and innovation (Chesbrough

& Tucci, 2004), to identify complementary products and services (Dushnitsky & Lenox, 2005b), and to anticipate emerging and potentially disruptive technologies (Dushnitsky, 2012). Essentially, for technology-based industries, both startups and CVC investors enter into the CVC relationship with the primary objective of accessing and leveraging each other's strategic resources and knowledge.

The interaction between startups and incumbents through CVC relation directly or indirectly facilitate knowledge spillovers (Paik & Woo, 2017), especially when their technological capabilities overlap (Ginsberg, Hasan, & Tucci, 2011). Several studies explicitly investigate the knowledge flow by tracking the patent citation data between established firms and their portfolio startups. Di Lorenzo & Van de Vrande (2019) found that startups increase backward citations of their investor's (Intel) patents after receiving CVC investments and after they hire an inventor from their investor. In the biotechnology context, Polidoro & Yang (2021) found that in their post-investment patent applications, CVC-backed startups increasingly cite their corporate investors' past patents.

Knowledge transfer and assimilation bring about innovation-related benefits for startups. Numerous studies found that CVC-backed startups exhibit a higher level of innovation compared to startups that solely receive funding from independent venture capitalists, because access to corporate investor's complementary assets allow startups to build on a corporate's prior knowledge (Alvarez-Garrido & Dushnitsky, 2016) and enable the transfer of tailored knowledge and resources (Park & Steensma, 2013). In addition, corporate investors provide greater industry knowledge because of the technological fit within the dyad and are more tolerant for failures rising out of innovative experimentation (Chemmanur et al., 2014).

In sum, the collaboration facilitated by CVC investments between startups and incumbents gives rise to the emergence of valuable learning synergies.

2.2.2 Corporate venture capital and competitive threats

Apart from the learning benefits examined after CVC relationship is formed, the competitive lens is offered primarily by researchers studying the antecedents of CVC tie formation. Since the realization of knowledge transfer and learning synergies essentially requires the disclosure of invention and information, there exists the potential risk that corporate investors may imitate and misappropriate startups' technologies once they are disclosed (Dushnitsky & Shaver, 2009; Katila, Rosenberger, & Eisenhardt, 2008; Kim, Steensma, & Park, 2019). As we mentioned earlier, the main objective of established corporations' CVC activities is to gain a window on technology (Benson & Ziedonis, 2009). Industry incumbents increasingly use CVC activities to monitor emerging technologies, to survey the technological landscape of startups, and to potentially preempt future rivalries. Indeed, Dushnitsky and Shaver (2009) found that the disclosure of inventions is often a prerequisite for receiving CVC investments.

We contend that the competitive concern becomes even more pronounced after the CVC deal, because the information asymmetry is reduced through the interaction between startups and investors, enabling them to gain a better understanding of the partner firm's technologies and research projects. In addition, technology is the primary source of competitive threats for technology-intensive industries, since startups and incumbents often compete to define dominant designs in the technological race (Chen et al., 2017). Hence, receiving CVC investments is figuratively described as 'swimming with sharks' (Colombo & Shafi, 2016; Katila et al., 2008; Hallen, Katila, & Rosenberger, 2014), because startups may face the dilemma between seeking learning benefits associated with sharing their technology and the need to protect themselves against potential opportunistic behaviors. Incumbents might indeed use strategically their CVC relationship with the startup to preempt future technological rivalry. In the following, we explore how the interplay of learning opportunities and competition dynamics is manifested through the technological positions of startups in relation to their CVC investors.

2.2.3 Corporate venture capital and startups' technological positioning

The notion of a technological landscape is based on the perspective that technology is comprised of numerous distinct technological fields (Jaffe, 1989). Within this framework, technological position is characterized as firms' research activities within specific technological subfields. It represents a dimension through which firms can differentiate from or align with other technology-based firms in the technological landscape (Aharonson, 2008). The difference between firms' technological positions is often measured as the technological distance[2] between a pair of firms. The underlying assumption is that firms actively choose their areas of research activities, which in turn determines their technological positions (Jaffe, 1986). Several factors can influence firms' choices in terms of technological positioning. One such factor is the presence of greater technological opportunities in alternative positions within the technological landscape (Jaffe, 1986, 1989). Additionally, firms may also undergo technological repositioning as a result of hiring scientists or experts who possess knowledge and expertise in technologically distant areas (Tzabbar, 2009). Critically, understanding the direction of how technological position moves over time is best achieved by considering the dynamics arising from interfirm relationships, which is the focus of the present paper.

We argue that the direction of technological reposition after CVC investment depends on the interplay of the learning opportunities and the competitive threats. Both factors are function of the pre-CVC technological distance between the startup and the investor, as we explain below.

[2] We use the original concept 'technological distance' and its operationalization developed by Jaffe (1986, 1989) throughout this paper. We are aware that there are other similar concepts such as 'technological proximity', 'technological similarity', 'technological overlap' etc. The nuanced differences among these concepts are out of the scope of this research.

Learning opportunities and technological distance. The learning opportunities arising from the CVC relationship push toward a converging development (Mowery et al., 1996, 1998), where the technological distance between firms diminishes, and they tend to occupy adjacent areas within the technological landscape.

Indeed, startups have strong motives to align their research focus with that of their CVC investors, and hence position themselves closer to their CVC partners. Entrepreneurial ventures often lack resources and industry experiences; therefore they must rely on external resources and knowledge to enhance and supplement their own innovative capabilities (Aldrich & Auster, 1986). By aligning their research interests with CVC investors, startups could gain access to corporations' resources such as in-house scientists, R&D facilities, manufacturing sites (Maula, 2007). Additionally, by innovating around the core technology of industry incumbents, startups not only enhance their own capabilities but also develop complementary technologies that incumbents may seek to license or acquire. This converging development of technological positions is consistent with prior studies that emphasize innovation benefits driven by knowledge transfer and an increased chance of recombinative innovation (Alvarez-Garrido & Dushnitsky, 2016; Dushnitsky & Lenox, 2005; Sabel & Di Lorenzo, 2022; Smith & Shah, 2013).

We argue that the learning effect is particularly pronounced when startups and CVC investors have an intermediate level of technological distance. Although a high level of technological similarity can facilitate the assimilation and integration of external knowledge, it also brings about information redundancy which is ineffective in generating new ideas and breakthroughs (Mowery et al., 1998). Conversely, firms whose knowledge base is dissimilar provide distinct capabilities and learning opportunities (Rosenkopf & Almeida, 2003), albeit they face problems with absorbing and effectively using knowledge of each other (Lane &

Lubatkin, 1998). Hence, it is proposed that technological distance has an inverted U-shaped relationship with learning outcomes.

Competitive threats and technological distance. Competitive threats arising from the CVC relationship tend to push toward a diverging development as it helps reduce the risks of future rivalry. On the one hand, young startups may be motivated to position themselves at a considerable distance from established incumbents as a precautionary measure to mitigate the risks of potential lawsuits and high costs associated with patent litigation (Lerner, 1995). Engaging in research in distant domains can also serve as a strategy to avoid direct competition with large incumbents once the technology is commercialized. On the other hand, CVC investors may attempt to redirect startups' R&D focus towards technological fields that are less similar to their own. In their qualitative study with corporate venture capitalists, one of CVC investors' unique practices identified by Souitaris & Zerbinati (2014) is to link the investee venture to the CVC's corporate parent during the post-investment deal monitoring. The primary objective is that "CVCs are interested in shaping the venture's trajectory toward a direction that is strategically meaningful for their parent." (Souitaris & Zerbinati, 2014: 338). When a startup has a high technological proximity with its corporate investor pre-investment, that is, a startup has novel inventions in the fields that are essential to a corporation's technological competencies, perceived rivalry and implicit competition might manifest (Chen, 1996), which can result in the initiation of competitive actions (Porac & Thomas, 1990). Additionally, CVC investors may use their investee startups to experiment with high-risk, high-return technologies, where the startup assumes the sole downside risk (Paik & Woo, 2017). Whether the decision to position far away from incumbents is a strategic choice made by startups or one that is "coerced" by CVC investors, it is motivated by a perceived rivalry and results in increased differentiation and specialization of technologies between startups and corporations.

The competitive threats arising from the CVC relationship are the highest when the pre-investment technological profile is most similar, and instead tend to progressively mute as the pre-investment technological distance increases.

By putting together how both the learning opportunities and the competitive threats vary with pre-CVC technological distance, we can derive specific predictions on how technological distance changes post-CVC investment. Figure 2.1 below illustrates our hypotheses. The center point within each circle denotes the fundamental technological field of a given CVC's corporate parent C_i. S_i illustrates a startup's technological position relative to C_i prior to the CVC deal, while S_i^* represents the relative position post-CVC. The space within the red circle represents the zone of competitive threat, whereas the space between the red and green circle delineates an optimal learning zone.

Figure 2.1 Three Hypotheses: The Effect of CVC on Technological Distance Change

The left panel of Figure 2.1 show cases when the pre-investment technological profile is close (technological distance is close to 0). When the technological distance pre-CVC investment is low, learning opportunities are limited because of technological similarity and information redundancy (Mowery et al., 1998), while the competitive threats are the most powerful because the startup is likely to develop inventions in fields that are essential to the corporation's technological competencies (Chen, 1996). Thus, the diverging development tends to prevail. This suggests that:

Hypothesis 1. When the pre-investment technological distance is low, CVC investments would increase the technological distance between startups and their investors' corporate parents.

Instead, the middle panel of Figure 2.1 illustrates cases when the technological distance pre-CVC investment is intermediate. Here the learning opportunities are at their maximum potential (e.g., Ahuja & Katila, 2001; Huo, 2021; Mowery et al., 1998; Müller & Zaby, 2019), while the competition threats, although not inexistent, are rather limited. The converging development tends therefore to prevail. This implies that:

Hypothesis 2. When the pre-investment technological distance is intermediate, CVC investments would decrease the technological distance between startups and their investors' corporate parents.

Finally, when the technological distance pre-CVC investment is high (technological distance is close to 1), as shown at the right panel of Figure 2.1, CVC investors are likely to prioritize financial objectives over strategic considerations. In such instances, there are both limited learning opportunities (Lane & Lubatkin, 1998) and competitive threats arising from the CVC relationship. Therefore, we predict that their technological positions will remain distant even after the CVC deal has been established.

Hypothesis 3. When the pre-investment technological distance is high, CVC investments would not change the technological distance between startups and their investors' corporate parents.

2.3 Data and methods

2.3.1 Sample

We build our sample from two major resources. To gather information about startups' financing history, we use Pitchbook, a novel and fast-evolving dataset that is reported to have better coverage and provide more accurate funding information (Retterath & Braun, 2020). In addition, Pitchbook is more transparent in terms of identification of general partners and fund names (Kaplan & Lerner, 2017), which is helpful in identifying corporate investors. We begin the sampling process by selecting all startups in the Information Technology (IT) sector that have received financing from corporate investors between 1995 and 2017. We chose the IT industry in this period because CVC programs and VC investments have surged since the mid-1990s due to technological progress and Internet-related new venture creation (Dushnitsky, 2012). This new wave of CVC investments also reflects established corporations' increasing use of CVC investments as an external source of innovation. We select startups that are headquartered in European EEA countries (including UK) and North America[3], since these countries share similar institutional environments and are most likely target destinations of corporate investors. In addition, to avoid confounding influences from multiple rounds of subsequent investors, we only consider a given startup's first time of CVC relationship formation. We further verified each corporate investor's parent company and eliminated investors whose parent is either a bank, a university, an asset management firm, an insurance company, or a government agency. This is consistent with prior research practices, since investments by these firms appear not to be motivated by technology-related strategic objectives (e.g., Dushnitsky & Lenox, 2005a; Kim & Park, 2017).

We obtained 4,812 startup-corporate dyads from Pitchbook. In the following, we tracked their patenting history using the European Patent Office's (EPO) PATSTAT Global dataset by conducting a systematic name-match between the two datasets. We first standardize all firm names in Pitchbook and PATSTAT, following the standardization procedures provided

[3] These countries are: Austria, Belgium, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States

by Arora, Belenzon, & Sheer (2021). The standardization allowed us to make the formatting of names consistent before matching the two datasets. We then used the fuzzy matching library 'RapidFuzz'[4] in python to automatically match similar names between the two datasets. At a final step, we manually verified each returned name and their headquarters to make sure that the matched names are the same entities. Since we rely on patent information to measure the technological distance, in order to be included in the sample, we require that both startups and corporations have filed at least one patent application prior to the CVC investments[5]. In order to study the change of technological distance prior to and after each investment relationship, we collect all patents filed by startups and corporations five years prior to and five years after a CVC deal.

In total, our data includes corporate-startup dyads formed between 1995 and 2017, with their patenting information observed up to five years after the year of CVC deal. Our sample startups are all founded between 1990 and 2017, and headquartered in Europe and North America. As we will explain in detail later, we also constructed a matched control sample of startups that are backed by independent VC investors. The final sample consists of 3,820 observations, with 1,910 unique corporate-startup dyads (955 treated and 955 control dyads respectively), observed twice (before and after receiving CVC investments), of which 797[6] are CVC-backed startups, and 642[7] are matched control startups that have received funding from traditional venture capitalists.

2.3.2 Measures

Technological distance. We measure *technological distance* between a startup and its corporate investor using patents filed five years prior to and five years after the CVC deal year.

[4] Program documentation page at: https://maxbachmann.github.io/RapidFuzz/

[5] This step resulted in 1,619 startup-corporate dyads. That means, about one-third of the dyads have at least one patent before CVC investments.

[6] There are more dyads than startups because some startups have more than one CVC investor.

[7] Some control startups are matched more than once to treated startups because they are matched on different deal years.

By studying a given firm's patenting activities in various technological fields, we can obtain a pair of firms' relative position in a multi-dimensional technological space. Since this study focuses on startups' change of technological positioning due to CVC investments, we use the corporate investor's pre-investment patents as the reference point. We construct two positions of startups in relation to its CVC investor: one based on all patent applications filed five years up to the CVC deal year, and another based on all patent applications five years after the CVC deal year. In this way, we can observe to what extent startups have changed their technological positioning in relation to its corporate investor after receiving the CVC investment.

We adapt the proximity measure developed by Jaffe (1986) and define the technological distance between any two firms as following:

$$Distance_{ij} = 1 - \frac{F_i F_j{}'}{(F_i F_i{}')^{1/2}(F_j F_j{}')^{1/2}}$$

where F is the vector of a given firm's technological profile pointing into the technological space. The vector represents a given firm's share of patents in each technology class. The latter part of the formula is a proximity measure, which is calculated as the cosine distance, also called the uncentered correlation, between any two firm pairings. The measure takes a range between 0 and 1, where 1 indicates a perfect overlap (vectors pointing to the same direction) and 0 no overlap (vectors are perpendicular). Hence, the greater the overlap between two firms' research interests, the closer they are positioned in the technological space. We subtract this proximity measure from one, in order to get the distance measure. In other words, the greater this proximity index, the lower the technological distance between firms. We chose this measure over other alternatives because it is considered as the best practice in previous research, it has been provided with the economic microfoundations, and more importantly, it is less sensitive to the way technological fields are aggregated (Bloom, Schankerman, & Van Reenen, 2013).

Several points are worth mentioning when calculating the measure of technological distance. Benner & Waldfogel (2008) raised concerns that technological distance calculated using samples with few patents or only the main patent class can be imprecise and biased. Hence, we follow their advice by aggregating all patents filed within five years of the CVC deal, rather than calculating the distance at firm-year level. In addition, instead of using only one patent class per patent, we included all patent classes assigned to a patent. Furthermore, we take into consideration which dimension of patent class we should use in the calculation. The IPC classification system[8] divides technology fields into eight sections (most coarsened) and approximately 75,000 subdivisions (finest division). For our analysis, we choose the classification at 4-character subclass level (in total 647 subclasses). We believe this is most appropriate for the present study, since all our startups and the majority of corporations are operating in the same industry. Hence, the division at subclass level is sufficiently distinct but not too detailed. Using the most finely partition can lead to inaccurate measures of distance (Benner & Waldfogel, 2008), while information is too coarse with aggregated classes (Aharonson & Schilling, 2016).

CVC relationship. Since our unit of analysis is a unique startup-corporate dyad, *CVC relationship formation* is a dummy that takes 1 if a startup has received investments from a corporate investor and 0 for matched control startup-corporate dyad. At startup-level, treated startups are those that received both VC- and CVC-financing, whereas control startups are solely VC-backed[9].

Control variables. Several covariates can influence the likelihood of a CVC relationship formation and startups' innovation capability. At startup-level, we control for *Startup age*, which is measured as the number of years from startup's founding year till the

[8] Edition 2022.01
[9] This is consistent with prior research (e.g. Alvarez-Garrido & Dushnitsky, 2016; Kim & Park, 2017), where receiving independent VC is treated as a baseline condition, so that we can reasonably assess the extra effect of receiving CVC investments.

CVC/VC deal year. Previous research uses this variable as a proxy for firm size and firm growth (e.g. Alvarez-Garrido & Dushnitsky, 2016; Pahnke et al., 2015), since longer-tenured startups tend to be more innovative. We also control for a startup's pre- and post-investment *Patent stock*, measured as the number of patent applications in distinct patent families within five years of the deal year. In entrepreneurial settings, patents are considered the most important resource and assets (Dushnitsky, 2012), especially for technology-related firms. The financial resources available to a startup can be important in driving the R & D process. Hence, we control for the natural log of *Cumulative Investment Amount* that a startup has raised. For covariates that are time-invariant, we control for the *Total Number of Investors* for a given startup, as proxies for a startup's quality. We also control for *Early Stage*, a dummy variable equals to 1 if a startup has received investments in its first three years of life. Startups in this early period of life are most malleable to the influences of external investors (Kim & Park, 2017).

2.3.3 Empirical methods

Our study focuses on how receiving CVC investments might shape a startup's technology position in relation to its investor. An intuitive analysis is to determine whether the technological distance before and after the CVC deal is significantly different from each other. However, since receiving CVC investments is not a random assignment, the statistical challenge remains that the technological distance between a startup and its CVC investor post-investment might change due to factors other than CVC investors' influences. We believe there are two major factors that need our attention. First, as commonly raised by previous research, we need to take into consideration the effect of selection into forming a CVC relation. For our study, CVC investors might select startups that are more malleable in changing their technological positioning during its growth. Second, there might exist some common technological trends in the focal industry so that some startups change fields of their innovative activities.

Matched samples. To address the concerns raised above, we combine Coarsened Exact Matching (Iacus, King, & Porro, 2009) with optimal pair matching (Hansen & Klopfer, 2006) to construct a carefully selected counterfactual group of startups, that are similar to treated startups in terms of firm characteristics, funding history, and most importantly, technological profile. The aim of the matching is to create matched pairs of startups pre-investment, where the control startup would have been eligible to receive investments from the same CVC investor as its treated counterpart.

Using a matching method to construct a control group has been used in previous research on venture capital research (e.g., Blevins & Ragozzino, 2018; Hsu, 2006; Pahnke et al., 2015; Polidoro & Yang, 2021). We chose Coarsened Exact Matching (CEM) over Propensity Score Matching because the latter has been questioned of increasing data imbalance, model dependence and hence bias (King & Nielsen, 2019). CEM allows us to temporarily coarsen the pre-selected matching covariates into reasonable categories, so that we can retain meaningful treated observations with a balanced control sample (Blackwell et al., 2009). The matching process in our study follows two steps. The first step is to use CEM matching to create a stratum for each treated startup with all possible control startups that fit the categories of the pre-selected matching covariates. The second step is to apply optimal pair matching within each stratum to select the pair with the shortest Mahalanobis distance of all covariates. We discuss these procedures in detail below.

We start by selecting potential control startups in the IT industry that have received funding from traditional venture capitalists but not CVC investors. In determining the matching covariates, we refer to research on antecedents of CVC relationship formation (Pahnke et al., 2015) and design the matching conditions as specified in Table 2.1: First, we exact match on startup location, i.e. the control startup should be located in the same European country or the U.S. state/Canadian province as the treated startup. Second, since funding availability may exhibit fluctuations, we require that the control startup should raise capital within a year of the treated startup, i.e. either in the same year, or one year prior to/after the fund raising of the treated startup. Third, we require that the treated and control startups have similar ages (within 3 years of age difference) while receiving the funding. Fourth, we consider the total number of patents filed by startups before receiving the funding (up to 10 within the total number of patents of treated startup). Last but not least, we select all potential control startups that have a similar technological profile (technological distance below 0.3) to that of treated startups. This would suggest that prior to receiving any funding, the treated startup and the control startup have patented a similar number of patents in similar technological fields. This further suggests that a control startup has similar technological distance to its hypothetical corporate investor as the treated startup. If no stratum is formed based on above criteria, i.e. no startups satisfy the above conditions for a given treated startup, then this observation is dropped out of our sample. Once we go through the above procedure, optimal pair matching was performed using the MatchIt package (Ho, Imai, King, & Stuart, 2011) in R, which calls functions from the optmatch package (Hansen & Klopfer, 2006). We show the assessment of the quality of matches in the Results section below.

Table 2.1 Pre-deal Characteristics for Matching Treated and Control Startups

Variable	(Exact/Coarsened) categories
Location	Exact same U.S. State / Canadian Province / European Country
Deal year	same year, one year before, one year after
Startup age at deal	within 3 years of age differences
Patent stock before deal	within 10 of patent number differences
Technological Distance	below 0.3

Difference-in-Difference. Once we have our matched pairs of treated and control startups, we investigate the effect of receiving CVC investments on the change of technological distance with the following regression equation:

$$Technological\ Distance_{ijt} = \beta_0 + \beta_1 CVC_{ij} + \beta_2 Post_t + \beta_3 CVC_{ij} * Post_t + controls_{ijt} + \varepsilon_{ijt}$$

where $Technological\ Distance_{ijt}$ is the technological distance between firm i and investor j before and after investments. Our main coefficient of interest is β_3, which indicates the difference of technological distance change between treated and control startups. Since we expect differing effects (diverging vs. converging vs. unchanged) depending on the distribution of technological distance before investments, for our hypothesis testing, we first run analyses on the full sample, then we stratify the sample to run separate analyses. For dyads with close technological profile pre-investment, we predict that the technological distance would increase, hence we expect β_3 to be positive (diverging effect); for dyads with an intermediate level of technological distance pre-investment, we predict that the technological distance would decrease, hence we expect β_3 to be negative (converging effect); further, for dyads with distant technological profile pre-investment, we expect β_3 to be insignificant (unchanged).

2.4 Results

2.4.1 Descriptive statistics

Before we start the main analysis, we report in Table 2.2 assessment of quality from our matching procedure. As mentioned in the previous section, the matched pairs in our study are geographically located within the same EU country and U.S. state/Canadian province. Furthermore, they have received financing within a one-year timeframe of each other. After matching, we found no significant differences in terms of startups' age when receiving the financing, startups' total number of patent applications before deal, and more importantly, there is no significant difference in technological distance with investors between treated and matched control startups.

Table 2.2 Matching Covariates T-Test Results

	N	Control	Treated	Diff.	St. Error	t-value	p-value
Startup Age	955	3.56	3.67	-.11	.13	-.85	.39
Patent Stock before deal[10]	955	6.5	7.09	-.59	.45	-1.3	.19
Tech. Distance before deal	955	.56	.55	.01	.01	.55	.57

We report our summary statistics and correlation results for the full sample in Table 2.3. Being backed by a corporate investor has a positive correlation with the number of investors, the cumulative amount received, as well as patent stock before and after the investment. This is consistent with prior CVC research (e.g. Alvarez-Garrido & Dushnitsky, 2016; Kim & Park, 2017).

[10] Note: This figure is slightly bigger than summary statistics reported in Table 2.4, because the count of patents used for matching considers all patents of a given startup prior to CVC deal, whereas the count of patents used for the calculation of distance considers patents filed five years prior to CVC deal.

Table 2.3 Descriptive Statistics and Correlation Matrix

	Mean	SD	1	2	3	4	5	7	8	9
1. CVC-Relationship	0.50	0.50	-							
2. Startup Age	3.62	2.78	0.02	-						
3. Early Stage	0.58	0.49	-0.02	-0.77*	-					
4. Investor Number	10.05	10.51	0.31*	0.02	-0.01	-				
5. Ln (Cumulative Amount Raised)	2.60	1.44	0.16*	0.27*	-0.21*	0.34*	-			
6. Tech. Distance (pre-deal)	0.55	0.32	-0.01	-0.06*	0.06*	-0.04	-0.08*	-		
7. Tech. Distance (post-deal)	0.57	0.32	-0.03	-0.05*	0.05*	-0.05*	-0.09*	0.91*	-	
8. Patents (pre-deal)	5.67	8.07	0.12*	0.14*	-0.16*	0.14*	0.43*	-0.05*	-0.03	-
9. Patents (post-deal)	6.34	20.19	0.08*	0.00	-0.04	0.30*	0.25*	-0.05*	-0.05*	0.37*

*Significant at the 5% level or higher.

We then show summary statistics for the treated and control startups respectively in Table 2.4. On average, our treated startups received their first CVC deal at age 3.67. Around 57.2% of our sample startups received CVC investments during its first three years of life. Treated startups have on average 13.3 investors, while control startups have 6.8 investors. The average technological distance of treated startups with their corporate investors before the CVC deal is 0.55, while the post-deal technological distance is around 0.56. On average, startups that received CVC investments have filed 6.6 patents five years prior to their first CVC deal, compared to 7.9 patents five years after the deal.

Table 2.4 Summary Statistics by CVC relationship

		Control			CVC		
	N	Mean	Min	Max	Mean	Min	Max
Startup Age	955	3.56	0	17	3.67	0	18
Early Stage	955	.59	0	1	.57	0	1
Investors Number	955	6.83	1	59	13.27	2	130
Ln (Cumulative Amount Raised)	955	2.32	-3.69	6.58	2.87	-2.79	6.40
Tech. Distance (pre-deal)	955	.56	0	1	.55	0	1
Tech. Distance (post-deal)	955	.58	0	1	.56	0	1
Patents (pre-deal)	955	4.7	1	54	6.59	1	84
Patents (post-deal)	955	4.8	0	239	7.89	0	263

2.4.2 Change of Technological Distance

Before we start the Difference-in-Difference analyses for the treated and control samples, we first show mean technological distance of both treated and control startups pre and post deal at different percentiles in Table 2.5. Since we matched treated and control startups' technological profiles, the pre-deal differences in technological distance is close to zero. However, there are systematic changes in the differences in the technological distance of the treatment and control startups post-deal, suggestive of effects of CVC on change of technological positions. As is evident in Table 2.5, the effect is heterogeneous at different levels of the distribution. The effect in the lower parts of the distribution is positive, indicating an increasing technological distance post-deal for CVC-backed startups. In the central parts of the distribution the effect is negative, indicating a decreasing technological distance post-deal for CVC-backed startups. In the uppermost part of the distribution, the effect is close to zero. This preliminary result is reassuring since it is consistent with our predictions.

Table 2.5 Distribution of Technological Distance

	Level	Differences		DiD
	Treated	Treated – Control		Treated – Control
	Pre-CVC	Pre-CVC	Post-CVC	Post-CVC – Pre-CVC
10th percentile	0,12	0,00	0,02	0,02
20th percentile	0,23	0,00	0,03	0,03
30th percentile	0,34	-0,01	0,01	0,02
40th percentile	0,43	-0,01	-0,05	-0,04
50th percentile	0,53	-0,01	-0,02	-0,01
60th percentile	0,65	0,01	-0,02	-0,03
70th percentile	0,77	-0,01	-0,04	-0,03
80th percentile	0,91	-0,01	-0,03	-0,02
90th percentile	1,00	0,01	0,00	0,00
Mean	0,55	-0,01	-0,02	-0,01

Difference-in-Difference. We begin by presenting results of the Difference-in-Difference estimates with matched startups on the full sample in Table 2.6. We include no controls in Model 1, time-variant controls only in Model 2, and all control variables in Model 3. Aggregating the full sample, there is no significant effect of CVC on change of technological positions. This conclusion would be misleading if we stop here and do not explore differential effects depending on the initial level of technological distance. In the next we explore the possibility of a heterogenous treatment effect.

Table 2.6 Differences-in-Differences Estimates (Full Sample)

	(1) Full Sample	(2) Full Sample	(3) Full Sample
CVC	-.008	-.006	.003
	(.015)	(.015)	(.015)
Post-deal	.026*	.057***	.04*
	(.015)	(.018)	(.021)
CVC × Post-deal	-.009	-.008	-.008
	(.021)	(.021)	(.021)
Startup Age		-.006***	-.003
		(.002)	(.003)
Patent Stock		-.001***	-.001*
		(.000)	(.000)
Investor Number			-.001
			(.000)
Ln (Cumulative Amount Raised)			-.000***
			(.000)
Early Stage			.009
			(.016)
Constant	.556***	.583***	.631***
	(.01)	(.012)	(.032)
Observations	3820	3820	3820
HQ Country FE			Yes
R-squared	.002	.007	.014

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

We then used two different ways to stratify our sample. The first way is to use the mean and standard deviation of the pre-investment technological distance. We code the pre-investment technological distance as high if the distance measure is one standard deviation above the mean, and we code it as low if the distance measure is one standard deviation below the mean. The rest of the sample is coded as intermediate. The alternative way is to trichotomize the sample into the upper quarter, the lower quarter, and the middle. Results for the three stratified samples are shown in Table 2.7, robust standard errors are reported in parenthesis. Model 1-3 report results on the subsample when the pre-investment technological distance is low (one standard deviation below the mean). Consistent with our first hypothesis, there is a significant (at 10% level) increase in technological distance, consistent with the diverging hypothesis. That is, compared to control startups, CVC-backed startups are more likely to move away from its investors' technological profile after receiving CVC investments. Specifically, the technological distance increases by 0.025, equivalent to a 17.86% increase for startups that position near their CVC investors. This effect holds when we include the control variables. Model 4-6 report results on the subsample when the pre-investment technological distance is at the intermediate level. Consistent with hypothesis 2, there is a significant (at 10% level) decrease in technological distance, suggesting that compared to control dyads, post-investment technological relation becomes more converging for CVC-backed pairs. Specifically, the technological distance decreases by 0.029, equivalent to an average decrease of 5%. Model 7-9 report results on the subsample where the pre-investment technological distance is high. As predicted, we did not find a significant effect, although Model 9 shows that having multiple investors and the number of patents has a negative effect on technological distance. We confirmed these results also using the alternative way to split the sample into the upper quarter, lower quarter, and the middle.

Table 2.7 Differences-in-Differences Estimates (Stratified Sample, OLS regression)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pre-TD Low	Pre- TD Low	Pre-TD Low	Pre-TD Intermediate	Pre-TD Intermediate	Pre-TD Intermediate	Pre-TD High	Pre-TD High	Pre-TD High
CVC × Post-deal	.027*	.026*	.026*	-.029*	-.029*	-.029*	0	0	0
	(.015)	(.015)	(.015)	(.017)	(.017)	(.017)	(.009)	(.009)	(.009)
CVC	.001	0	-.001	0	.001	.005	.002	.003	.007*
	(.007)	(.007)	(.007)	(.011)	(.011)	(.011)	(.004)	(.004)	(.004)
Post-deal	.027***	.041***	.028**	.045***	.055***	.052***	-.015**	-.023***	-.023***
	(.009)	(.01)	(.012)	(.012)	(.015)	(.019)	(.007)	(.007)	(.009)
Startup Age		-.003***	0		-.002	-.001		.001*	.001
		(.001)	(.002)		(.002)	(.003)		(.001)	(.001)
Patent Stock		0	0		0	0		-.001**	0.000**
		(0)	(0)		(0)	(0)		(0)	(0)
Investor Number			0			0			-.001**
			(0)			(0)			(0)
Ln (Cum. Amount Raised)			-.003			-.005			-.002
			(.003)			(.004)			(.001)
Early Stage			.019*			-.001			-.003
			(.01)			(.014)			(.007)
Constant	.12***	.13***	.159***	.535***	.543***	.562***	.971***	.968***	.956***
	(.005)	(.006)	(.023)	(.008)	(.01)	(.028)	(.003)	(.004)	(.016)
Observations	812	812	812	2090	2090	2090	918	918	918
HQ Country FE			Yes			Yes			Yes
R-squared	.042	.049	.065	.008	.009	.011	.012	.02	.029

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

2.4.3 Robustness checks

In the section above, we used a standard DiD estimator to examine the average effect in the three stratified samples. To test the robustness of our results, we ran separate analyses and use alternative specifications. First, since our dependent variable technological distance is a rate that ranges between zero and one, we repeat our analysis in the stratified sample using a fractional response model (Papke & Wooldridge, 1996; Wooldridge, 2010). Instead of ordinary least squares, fractional response models use quasilikelihood estimators. These models are typically applied to data when the outcome of interest is bounded between zero and one, such as participation rate, or the Gini coefficient. We also include firm and state/country level fixed effects. Table 2.8 reports our results. The signs of the coefficients are the same as our main analysis.

Table 2.8 Difference-in-Difference (Stratified Sample, Fractional Response Model)

	(1) Pre-TD Low	(2) Pre- TD Low	(3) Pre-TD Low	(4) Pre-TD Intermediate	(5) Pre-TD Intermediate	(6) Pre-TD Intermediate	(7) Pre-TD High	(8) Pre-TD High	(9) Pre-TD High
	TD	TD	TD	TD	TD	TD	TD	TD	TD
CVC × Post-deal	0.110*	0.106	0.169***	-0.074*	-0.074*	-0.144**	-0.011	-0.009	-0.138
	(0.064)	(0.065)	(0.054)	(0.044)	(0.044)	(0.057)	(0.106)	(0.106)	(0.089)
Post-deal	0.127***	0.189***		0.114***	0.138***		-0.193**	-0.292***	
	(0.039)	(0.047)		(0.032)	(0.038)		(0.075)	(0.090)	
Startup Age		-0.012***	0.012**		-0.005	0.011**		0.019*	-0.012
		(0.005)	(0.005)		(0.004)	(0.005)		(0.011)	(0.011)
Patent Stock		0.001	0.002		-0.001	-0.000		-0.005***	-0.006**
		(0.001)	(0.001)		(0.000)	(0.001)		(0.002)	(0.002)
Investor Number			0.002			-0.001			-0.006
			(0.001)			(0.001)			(0.004)
Ln (Cum. Amount Raised)			-0.017			-0.015			-0.030
			(0.012)			(0.010)			(0.019)
Early Stage			0.134***			0.074**			-0.221***
			(0.044)			(0.031)			(0.080)
Constant	-1.177***	-1.131***	-1.248***	0.089***	0.108***	0.307**	1.899***	1.855***	2.139***
	(0.023)	(0.031)	(0.285)	(0.020)	(0.025)	(0.147)	(0.038)	(0.051)	(0.293)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects			Yes			Yes			Yes
Year Fixed Effects			Yes			Yes			Yes
Observations	812	812	812	2,090	2,090	2,090	918	918	918

Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

2.4.4 Supplemental Analyses

We conducted some supplemental analyses to further investigate the implications of technological distance change on startups' innovativeness and exit outcomes after CVC-deal. For this purpose, we only considered CVC-backed startups. We coded those startups that decreased (increased) their technological distance with their CVC-investors as converging (diverging) startups. Table 2.9 shows the results. In Models 1-2, we use a negative binomial specification to estimate the effect of divergence/convergence on startups' number of patent applications after CVC deal. Our findings reveal a notable adverse impact on diverging startups, indicating that startups that position themselves further away from their CVC investors after the deal tend to file fewer patents compared to converging startups. This suggests that diverging startups are less likely to benefit from the knowledge provided by CVC investors. In contrast, converging startups exhibit greater levels of innovation, indicating the presence of learning benefits derived from their CVC investors. In Models 3-6, we use a Cox Hazard model to estimate the effect of convergence/divergence on startups' time to successful exit. We classified both acquisitions and going public as successful events and measured the time to success from the year of the CVC deal until 2022, the end of our observation period. Our findings indicate that diverging startups achieve successful exits in significantly less time compared to converging startups. Additionally, diverging startups are approximately 24% more likely to experience a successful exit compared to converging startups. We propose two potential explanations for this intriguing finding. Firstly, it is plausible that diverging startups are less reliant on the technological knowhow provided by their CVC investors. Secondly, startups that technologically differentiate themselves from their CVC investor may be perceived as more appealing to potential acquirers.

Table 2.9 Supplemental Analysis with Negative Binomial and Cox Hazard Models

	(1) Post-deal Patents	(2) Post-deal Patents	(3) coefficient	(4) Hazard Ratio	(5) coefficient	(6) Hazard Ratio
TD increase	-.183	-.49***	.27**	1.31**	.217*	.1.243*
	(.117)	(.103)	(.121)	(.158)	(.127)	(.158)
Startup Age		-.105***			.025	1.026
		(.02)			(.025)	(.025)
Pre-deal TD		-.391**			-.009	.991
		(.176)			(.223)	(.221)
Pre-deal Patents		.06***			.006	1.006
		(.005)			(.006)	(.006)
Total No. Investors		.027***			-.01**	-.990**
		(.004)			(.005)	(.005)
Ln (Cum. Amount Raised)		-.163***			.121**	1.123**
		(.035)			(.059)	(.005)
Post-deal Patents					.011***	1.011***
					(.002)	(.002)
Constant	2.782***	2.684***				
	(.088)	(.164)				
Observations	491	491	491	491	491	491
R-square	.001	.073	/	/	/	/
Log likelihood			-1569.388		-1551.154	

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

2.5 Discussion

This paper examines the change of technological distance between a startup in relation to its CVC investor after CVC-relationship formation. Using information about the number of patent applications in various technological fields, we compare a startup's innovation focus before and after CVC investments with respect to the technological profile of its CVC investor. We examine the interplay between two different mechanisms: the learning mechanism, which implies knowledge flow and technological exchange within the dyad; and the competition mechanism, which implies a differentiation with regard to R&D focus and technological competencies. We argue that the interplay of these two mechanisms manifests in the technological positions between a startup and its CVC investor prior to the CVC deal. Our findings on how receiving CVC investments changes the technological distance are as follows: a startup whose technological profile is highly close to that of its CVC investor pre-investment tends to move away from the technological fields of its investor, i.e. the technological distance increases within the dyad after CVC relationship formation; by contrast, the technological distance tends to decrease to some extent when the pre-investment technological distance is moderate; further, a startup whose technological profile is highly distant from that of its corporate investor pre-investment tends to remain distant from the technological fields of its investor. Overall, these findings suggest that the competition concern prevails the learning effect when there might exist substitution threat; whereas learning benefits dominate when their technological capabilities are not too similar but complementary; finally, both learning opportunities and competition threats are limited when the technological profile of a startup and its corporate investor is too far away from each other.

Through our research, we make a valuable contribution to the existing knowledge regarding the impact of CVC investments on the innovative performance of startups. While previous studies have primarily focused on evaluating the post-investment innovation rates of startups (e.g., Chemmanur et al., 2014; Alvarez-Garrido & Dushnitsky, 2016; Park & Steensma, 2013; Uzuegbunam, Ofem, & Nambisan, 2019), we take a distinct approach by explicitly exploring the extent to which the technological positions of startups evolve in relation to their CVC investors. In this regard, we complement the existing understanding by examining the specific areas of focus in startups' post-deal technological activities.

We bring forward two countervailing mechanisms that emerge from CVC relationships: learning opportunities and competition threats. Our research reveals that when the learning mechanism dominates, there is a noticeable convergence in the technological positions of startups and their CVC investors. This finding supports previous studies that highlight the presence of knowledge flows and beneficial learning synergies between startups and their CVC investors, facilitated by the CVC relationships (e.g. Polidoro & Yang, 2021; Smith & Shah, 2013). In addition, our finding about a *divergence* in technological positions underscores the significance of the competitive lens alongside the learning benefits when examining CVC relationships. This is also consistent with the finding that CVC-backed startups draw less on their CVC investors' knowledge (Di Lorenzo & Van de Vrande, 2019).

Our supplemental findings on how changes in technological positions impact startups' innovative performance offer valuable insights that help explain the inconsistent findings in previous studies regarding the innovative benefits brought by CVC investors. While some scholars found that CVC-backed ventures are more innovative than those funded solely by independent VC, other scholars found that CVCs may impede startups' technological developments. They concede that helpful resources exist in corporate investors, but these resources are either hardly made accessible to startups (Pahnke et al., 2015), or they could constrain startups in making pathbreaking inventions (Balachandran, 2019; Polidoro & Yang, 2021). Adding to this debate, our results present a compelling argument indicating that startups that converge their research interests with those of their CVC investors experience greater innovative benefits compared to startups that diverge from the research areas of their CVC investors.

Our findings provide additional insights into the implications of CVC investments on startups' exit outcomes. Notably, Park and Steensma (2012) discovered that CVC-backed startups have a higher likelihood of going public, particularly when they require specialized complementary assets. In contrast, Kim and Park (2017) found that startups receiving CVC funding within their first three years are less likely to go public. Our study further examines the diverging and converging dynamics in technological positions within startups and their CVC relationships. Interestingly, our findings suggest that diverging startups, those moving away from the research areas of their CVC investors, are more likely to experience a successful exit, either through acquisition or initial public offering (IPO), in a shorter time frame.

Overall, our findings highlight the complex relationship between CVC investments, startups' technological trajectory, as well as innovative performance and exit outcomes. They underscore the need to consider the specific dynamics brought about by startups' technological positioning when analyzing the consequences of CVC investments on startups.

Our study also brings to attention the broader implications of CVC investments for technology management and industry competition dynamics. Extant literature on technological disruption argue that technological breakthroughs are generally driven by new entrepreneurial firms, whereas established incumbents focus on incremental innovation. This literature generally acknowledges that established firms are vulnerable and often hard to escape the fate of being replaced by startups with disruptive technologies (e.g. Birkinshaw, Bessant, & Delbridge, 2007; Christensen & Bower, 1996). However, recent trends show that an increasing number of established firms employ CVC units as an arm for external search and for monitoring emerging technologies. They invest increasingly earlier, take more leads in deals, and acquire bigger stakes in deals (Silicon Valley Bank, 2021). This might suggest that large established incumbents will gain increasing power over startups, and hence benefit in later competition landscapes. In this regard, we draw a cautious connection with the recent observation of "killer acquisition" (Cunningham, Ederer, & Ma, 2021), where large corporations acquire innovative startups with the intention to discontinue startups' innovation projects and hence preempt future competitions.

Consequently, this research opens up several avenues for future research. Previous research suggests that corporate investors are less likely to acquire startups that they invested in (Benson & Ziedonis, 2010). We conjecture that the change of technological relationship might provide an explanation. In this regard, we see potential for future research to unpack the interplay between established corporations' CVC activities and acquisition strategies. In addition, although we uncovered suggestive evidences that corporations direct startups' innovative focus in differentiated technological fields, future research could explore whether and when startups are 'forced' to diverge, or if it is an arrangement mutually negotiated by startups and corporations. On the other hand, qualitative research from prior studies suggest that investors can put pressure on startups to align its technology agenda with the interests of the established firm, even if doing so could have adverse financial implications for startups (Katila et al., 2008). Finally, understanding the implications of CVC in the broad framework of entrant-incumbent dynamics is an important topic for future research. We hope future research will explore the interconnection between corporate venture capital and startup-incumbent competition dynamics.

Chapter 3 Venture Capital and Entrepreneurial Activities in a Nascent Industry

3.1 Introduction

Entrepreneurial activities play a pivotal role in driving innovation, fostering economic growth, and creating employment opportunities. Pioneering startups, such as Uber, Airbnb, Tesla, Netflix, PayPal, not only sparked but also subsequently dominated emergent industries (Zuzul & Tripsas, 2020). A salient commonality among these companies lies in their success in securing venture capital (hereafter, VC) financing at early-stage of their venture life.

There is an ongoing interest among both academics and practitioners in understanding how VC contributes to firm growth and to economic development at large (see Da Rin, Hellmann, & Puri, 2013 for a review). Anecdotal accounts suggest that the emergence and development of industries including semiconductor, IT, and biotechnology has been propelled by the readily available risk capital for new startups in such sectors (Nanda, Younge, & Fleming, 2015). Furthermore, post-investment activities by professional VC firms provide portfolio companies with an early advantage when competing with non-VC-backed counterparts, because VC-backed startups are shown to be more innovative (e.g., Hsu, 2006; Reuer & Devarakonda, 2017), better at organizing (e.g., Hellmann & Puri, 2002; DeSantola, Gulati, & Zhelyazkov, 2023), and achieve superior outcomes in product markets (e.g., Chemmanur, Krishnan, & Nandy, 2011; Grilli & Murtinu, 2014; Hellmann & Puri, 2000).

Despite the large literature that explore various ways in which VC provides “added value”, empirical evidence on how VC systematically influences dynamics in a nascent industry has been relatively scarce. This paper addresses this gap by studying the role of VC investments in affecting entry pattern and market positioning in the nascent plant-based food and beverage industry. “Plant-based” refers to food products that use plants instead of animal sources as ingredients (for a broader understanding of this food technology, see He, Evans, Liu, & Shao, 2020; Rubio, Xiang, & Kaplan, 2020). In contrast to conventional vegetarian food producers, plant-based foodtech startups employing novel technologies aim to biomimic the texture and taste profile of traditional meat and dairy products. Over the past decade, this nascent industry has attracted significant attention from aspiring entrepreneurs and venture capitalists. As we detail in the subsequent sections, the number of companies operating in this industry has surged nearly nine-fold, from approximately 100 producers before 2008 to more than 900 by the end of 2022. Similarly, there has been a sustained interest in venture capital within this emerging industry, marked by a consistent trend of annual deal count nearly doubling on average each year.

We explore two primary questions regarding the role of VC in influencing entrepreneurial activities. First, how do VCs' evolving investment strategies during the emergence of this nascent industry change entrepreneurs' entry decisions over time? We rely on the framework of entrepreneurial opportunity (Davidsson, 2015), as well as the structure of the VC industry (Janeway, Nanda, & Rhodes-Kropf, 2021) to make our predictions. The formation of a new venture idea is often shaped by external circumstances, referred to as "External Enablers" (Davidsson, 2015), the nature of which concurrently influences how would-be entrepreneurs assess the favorability of the new venture idea. We propose that overall VC interests, as a financial-channel "External Enabler", induce entry in a nascent industry by making the new venture idea more salient and favorable. However, this effect will be dampened when VC interests shift more towards financing existing portfolio companies through follow-on deals. Despite the sustained presence of VC interests in the nascent industry, the challenge of securing initial investments intensifies, deterring further entry of new startups.

Our second question explores how VCs contribute to shape startups' product positioning for wider market acceptance. We link VC practices with theory on institutional logics (Dalpiaz, Rindova, & Ravasi, 2016; Durand, Szostak, Jourdan, & Thornton, 2013) and market evolution (Dolbec, Arsel, & Aboelenien, 2022; Ertimur & Coskuner-Balli, 2015). We propose that VCs help portfolio startups effectively manage and combine multiple institutional logics in framing their innovative offerings. The objective is to capitalize on emerging trends in the broader social environment and to tap into different consumer segments, thereby broadening the product appeal.

To test these predictions, we compiled a unique panel dataset of global startups entering the nascent plant-based industry. We drew a sample of startups with primary focus on plant-based protein from the company database of the Good Food Institute, a major mission organization advocating for alternative protein. We cross-referenced the sample of startups in three mainstream financing datasets (Pitchbook, Crunchbase, and CBinsights) to obtain startups' funding history. To further examine how startups' positioning evolve over time, we scraped the historical websites of our sample startups from the Internet Archive. We obtained a screenshot per year for each startup and extracted the text data from these websites. For the analysis on entry pattern, we employed a panel conditional fixed effect Poisson estimation at the country-protein-year level. In examining startups' adoption of institutional logics, we employed a panel event study to compare shifts in their positioning subsequent to venture capital investments.

Descriptive trends and findings from regression analysis support our theoretical framework. We observed a positive effect of VC interests on the number of new entries into the nascent industry. Notably, this effect diminishes as the frequency of follow-on deals exceeds that of initial investments. Furthermore, compared to startups pre-VC investments and those without VC backing, we observed an increase in the number of institutional logics on the websites of startups post-VC investments.

We make three primary contributions to extant literature. First, we present empirical evidences supporting the notion that VC booms (Janeway, Nanda, & Rhodes-Kropf, 2021) in a nascent industry stimulate entrepreneurial entry (Mollica & Zingales, 2007; Samila & Sorenson, 2011; Popov & Roosenboom, 2013). Further, taking into account the structure of multi-staging and lifecycle of closed-end funds in the VC industry, we introduce a more nuanced framework that outlines how VCs' shift in focus towards follow-on deals within a nascent industry may deter entry (Cestone & White, 2003). Second, we add to the discussion about how VCs help startups in attaining superior product market outcomes (Chemmanur et al., 2011; Grilli & Murtinu, 2014). We propose that VC-backed companies are more inclined to adopt a broader market positioning to garner wider customer acceptance. This approach becomes particularly relevant when introducing new products initially targeted at a niche market. Third, we contribute to the entrepreneurship literature (Davidsson, 2015; Shane, 2012) by underscoring the essential role played by VC in the entrepreneurial process (Kerr, Nanda, & Rhodes-Kropf, 2014). We argue that VCs extend beyond being mere financial capital providers; they significantly shape entrepreneurial entry decisions and influence the formulation of entrepreneurial strategies.

3.2 Literature

3.2.1 The paradox of venture capital and entrepreneurial entry

What drives *entrepreneurial* entry in a *nascent* industry characterized by inherent technological and demand uncertainties? Macroeconomic environments such as business cycles (e.g., Konon, Fritsch, & Kritikos, 2018), technological advancements (e.g., Eckhardt & Shane, 2011), institutional norms (e.g., Sine & Lee, 2009; York & Lenox, 2014), industry structure and population ecology (e.g., Carroll & Swaminathan, 2000) all play a role in eliciting new venture attempts. Moreover, the rising awareness and demand for sustainability have triggered increased new business establishments within moral markets that address pressing social and environmental problems (Vedula, Doblinger, Pacheco, York, Bacq, Russon, & Dean, 2022). Collectively, research from these various streams underscore the essential role of *contextual* factors in shaping the identification and exploitation of entrepreneurial opportunities (Shane, 2012; Shane & Venkataraman, 2000). In this paper, we propose another increasingly important yet understudied financial-channel factor influencing entrepreneurial activities in a nascent industry: the evolving investment strategies of venture capital.

Venture capital has become an indispensable component in the modern entrepreneurial ecosystem. For young, innovative startups, VCs provide the essential capital, network connections, and strategic guidance required to transform an idea into a viable business and to facilitate the scaling process. These invaluable resources are often challenging to acquire through traditional financial channels. Findings indicate that VCs not only effectively screen startups with high growth potential (e.g., Engel & Keilbach, 2007), but also nurture startups through post-investment activities. Beyond the provision of capital, VC has been found to foster innovation and technology development (e.g., Hsu, 2006; Reuer & Devarakonda, 2017), to elevate the degree of professionalization (Hellmann & Puri, 2002), to speed up the commercialization process (Hellmann & Puri, 2000), and to accelerate sales growth (Grilli & Murtinu, 2014). Moreover, the involvement of venture capitalists serves as a powerful signal, attesting to the quality and growth potential of startups (Ragozzino & Reuer, 2007).

These touted benefits of securing VC funding have been associated with the success of numerous startups. As of 2021, the seven largest U.S. companies by market capitalization, including Apple, Microsoft, Amazon, received most of their early-stage external funding from VCs (Gornall & Strebulaev, 2022). Moreover, VC-backed companies constituted 41% of the overall market capitalization and were responsible for 62% of the R&D expenditures of public companies in the United States (Gornall & Strebulaev, 2021). Looking at the economy at large, this association between a thriving VC industry and the rapid growth of innovative startups has motivated the discussion and formulation of national and EU-wide policies aimed at fostering and supporting VC investments (Ständer, 2017; Quas et al., 2022). Indeed, from a demographic point of view, the volume of VC activities has been associated with broader economic indicators such as new firm establishments (Mollica & Zingales, 2007; Popov & Roosenboom, 2013; Samila & Sorenson, 2010, 2011), job creation (Puri & Zarutskie, 2012), and increased income (Samila & Sorenson, 2011).

These findings prompt us to question the ways in which VCs might shape aspiring entrepreneurs entering an emerging industry. Anecdotally, VC interests have been highly concentrated in certain sectors, notably software and biotechnology (Lerner & Nanda, 2020). This concentration has, in turn, been linked to the overarching growth and development of these industries. In this study, we bridge literature on venture capital, entrepreneurship, and the temporal dynamics in a nascent industry to theorize about how the evolving investment strategies of venture capital in a nascent industry impact entry pattern.

3.2.1.1 How does VC stimulate entrepreneurial entry in a nascent industry?

To facilitate our arguments, we employ the framework proposed by Davidsson (2015), which delineates three interrelated constructs to clarify the concept of "entrepreneurial opportunity". The focal point of our research is the construct of "External Enablers", referring to external, temporal circumstances that significantly influence the initiation of new ventures. It's worthwhile to note that these external circumstances, such as economic or institutional environments, can vary in favorability, with both positive and negative conditions impacting entrepreneurial attempts. We propose that the availability of VCs, as one type of external enablers, would stimulate entry in a nascent industry by facilitating the identification and recognition of a "New Venture Idea", i.e. the content of the entrepreneurial opportunity, and by enhancing the level of "Opportunity Confidence", i.e. the favorability of the entrepreneurial opportunity.

VC and New Venture Ideas. New Venture Ideas are "imagined future ventures" that provide products and services to potential markets or users (Davidsson, 2015). We propose two potential mechanisms through which VC interests contribute to the formation of new venture ideas. First, the attention and prominence given to the nascent industry by venture capitalists can extend to a broader set of external stakeholders, such as other investors, media outlets, and aspiring entrepreneurs actively seeking market opportunities. The investments made by VCs in emerging market segments often act as a signal, indicating a need for innovation or the presence of a market gap. This, in turn, serves as inspiration for entrepreneurs to generate business ideas aimed at addressing these opportunities. Second, VCs can encourage more founding via spin-offs from their investment portfolios (Samila & Sorenson, 2011). Many entrepreneurs initiate their own businesses after gaining experience and exposure within a VC-backed company. The tacit knowledge and networking opportunities with potential investors acquired during employment at a VC-backed company can prompt aspiring entrepreneurs to start their own businesses.

VC and Opportunity Confidence. In addition to the formation of new venture ideas, the likelihood of pursuing an entrepreneurial opportunity is frequently contingent on the perceived favorability of that opportunity. We argue that there are two potential mechanisms of how VCs influence would-be entrepreneurs assess the favorability of an entrepreneurial opportunity. First, VCs' interests can serve as a compelling motivator for would-be entrepreneurs that are constrained by financial resources (Samila & Sorenson, 2011). Especially in nascent industries where the technology lifecycle is young, entrepreneurs may view VC interests as an elevated likelihood of securing the initial funding needed to transform their ideas into viable businesses. Second, high levels of uncertainty are a defining characteristic of nascent industries, encompassing technological, demand, ecosystem, and institutional dimensions (Moeen, Agarwal, & Shah, 2020). Given that uncertainties constrain entrepreneurs in fully recognizing the complete range of choices and the likelihood associated with each potential outcome (Knight, 1921), the mitigation of these uncertainties becomes a critical factor for evaluating and exploiting an entrepreneurial opportunity (Shane & Venkataraman, 2000). Venture capitalists, as professional investors, often conduct in-depth market research to identify emerging trends and market opportunities. Their interests in a nascent industry could signal market validation and, to some extent, alleviate the "demand uncertainty about the viability of the new industry" (Agarwal & Bayus, 2004). This validation is especially important during the initial stage of an industry, where the market reaction to the proposed products and services remains unobservable. Therefore, the involvement of venture capitalists in a nascent industry could enhance the perceived confidence in entrepreneurial opportunities and subsequently lead to increased entry into the market.

Overall, we hypothesize that:

Hypothesis 1. There is a positive association between VC funding and subsequent founding rate in a nascent industry.

3.2.1.2 How does VC deter entrepreneurial entry in a nascent industry?

While it seems intuitive that increased capital availability in a market would naturally encourage entry, a more in-depth examination of venture capitalists' investment strategies and objectives may paint a more nuanced picture. Theoretically, Cestone & White (2003)'s model shows that in addition to product-market competitions, financial channels may also prompt entry deterrence. We build on this argument and propose that the assessment of the favorability of entrepreneurial opportunities will change over time as VCs' investment strategies evolve with the expansion of a nascent industry. More specifically, as VCs direct follow-on investments to a few successful startups that have emerged from the initial portfolio, funding available to new entrants is likely to decrease. This difficulty in securing funding will diminish the *Opportunity Confidence* of potential entrepreneurs, thereby deterring new firms entering the market.

It is well established that VCs engage in stage financing (Tian, 2011), where early-stage startups typically receive a modest initial capital injection, and subsequent capital is provided through follow-on deals. In the nascent stage of an industry's development, even though VCs may find an emerging sector appealing, accurately evaluating the true potential of early-stage startups proves to be challenging. Consequently, it is likely that VCs adopt a "spray and pray" strategy (Ewens, Nanda, & Rhodes-Kropf, 2018) during industry emergence, offering limited funding and guidance to a number of early-stage startups, most of which, however, will be abandoned later. This is consistent with the finding that VC-backed startups only show lower rate of failing during the first few years after first VC investments, compared to non-VC-backed counterparts (Puri & Zarutskie, 2012). After this timeframe where VCs "allow" its portfolio companies to grow, only the ones with the most growth potential will be continued.

Hence, with the growth and expansion of a nascent industry, it is expected that the deal structure of VCs will shift from initial investments in numerous startups to follow-on deals focused on a smaller number of ventures. In addition, at this stage of industry development, VCs are also less incentivized to allocate funding to new entrants, especially those with the potential to emerge as competitors to their existing portfolio companies. To sustain this elevated barrier to entry, previous research suggests that the widespread practice of deal syndication may even serve as a coordination mechanism among various VC investors, effectively limiting the entry of potential rivals into the industry of their portfolio startups (Toldrà-Simats, 2012).

Based on these arguments, we hypothesize that:

Hypothesis 2. Increases in the percentage of VC follow-on deals attenuate the positive impact of VC funding on founding rate.

3.2.2 VC on competitive positioning: Multiple institutional logics

Previous studies indicate that VC firms are actively shaping portfolio companies' strategies aimed at fostering rapid growth (e.g., Hellmann & Puri, 2000). From a technological improvement perspective, VCs facilitate exchanges of innovation resources (González-Uribe, 2020) and enable R&D partnerships (Reuer & Devarakonda, 2017) among their portfolio companies. They also "push" companies engage in Make-And-Buy innovation strategies (Da Rin & Penas, 2017). These endeavors contribute to enhancing the performance of startups' novel technologies, thereby paving the way for broader adoption in the market. At the product market level, VCs assist startups in building distribution channels by providing access to extensive networks of business contacts (Hochberg, Ljungqvist, & Lu, 2007), including suppliers and potential customers. Additionally, obtaining investments from reputable VCs can serve as a significant boost to brand awareness, attesting to the quality of the startup (Ragozzino & Reuer, 2007).

We suggest an alternative channel through which VCs contribute to portfolio companies attaining superior product market performance: the effective navigation of the institutional environment and combining institutional logics as strategic resources to gain broader market acceptance. Institutional logics are "socially constructed, historical pattern of material practices, assumptions, values, beliefs, and rules" (Thornton & Ocasio, 1999: 804) that shape the cognitive and behavioral orientations of individuals and organizations in a given social context. Changes in institutional environments can drive market transformation and evolution (Dalpiaz, Rindova, & Ravasi, 2016; Dolbec, Arsel, & Aboelenien, 2022). For example, the growing awareness of environmental issues and climate change has facilitated the emergence of a new logic of sustainability. Combining and including this logic can serve as a distinct business strategy to attract and gain legitimacy among environmentally conscious consumers (Grinevich, Huber, Karataş-Özkan, & Yavuz, 2019).

A nascent industry is characterized by a limited collective understanding of fundamental aspects related to a novel product (Navis & Glynn, 2010). When entering a nascent industry, it becomes crucial for entrepreneurs to identify and strategically align themselves with prevailing discourses or practices in the external environment (Durand et al., 2013). These logics become strategic resources as they influence the competitive positioning of startups and may have implications for their survival and growth.

Previous research has increasingly shown that multiple logics coexist in a lot of markets (e.g., Greenwood, Raynard, Kodeih, Micelotta, & Lounsbury, 2011; Lee & Lounsbury, 2017). Successfully incorporating elements from diverse institutional logics could potentially lead to endorsements from a broader spectrum of stakeholders, such as different segments of consumers and types of investors (Greenwood et al., 2011; Pache & Santos, 2013). For instance, in their study of rhetorical strategies employed by architect firms when competing for client projects, Jones & Livne-Tarandach (2008) found that the use of multivalent keywords, which integrate different institutional logics, enables firms to appeal to the diverse interests of various audiences. Similarly, in the study of the U.S. yoga market, Ertimur & Coskuner-Balli (2015) found that a generalist brand would adhere to all four logics available in the field --- spirituality, medical, fitness, and commercial --- especially when they pursue aggressive growth strategies.

We argue that the presence of venture capital helps VC-backed startups strategically combine and effectively utilize multiple institutional logics within a nascent market. To begin with, startups may grapple with limited resources and attention, especially when confronted with multiple institutional logics that bring distinct meaning systems and diverse demands (Greenwood et al., 2011). Moreover, effectively organizing when contending with potentially competing goals presents unique challenges (Battilana & Lee, 2014). The infusion of venture capital and strategic guidance from venture capitalists could empower startups to explore emerging logics, potentially challenging established norms and extending the boundaries of their original market niche. Second, VCs are rational investors that respond to public market signals when evaluating investment opportunities (Gompers, Kovner, Lerner, & Scharfstein, 2008). Anecdotally, VCs actively screen shifts in the technological, institutional, and regulatory environment to enhance their decision-making processes and adjust their portfolios. Consequently, when a novel institutional logic emerges, VCs may prompt portfolio companies in its adoption and incorporation, in order to capitalize on emerging trends in the broader social context. Third, leveraging multiple institutional logics allow startups to broaden their appeal, reaching a more extensive audience and transcending their initial niche. By tapping into different customer segments and adapting to dynamic market trends, startups can achieve faster and higher growth, aligning with the imperative of providing substantial returns to VC investors within a relatively short timeframe.

Based on these arguments, we hypothesize:

Hypothesis 3. Startups are more likely to adopt multiple institutional logics to frame their products following VC investments.

3.3 Research Context: The Global Plant-based Food and Beverage Industry

Our research context is the global plant-based food and beverage industry. As its name suggests, plant-based producers primarily use plants to replace animal inputs[11] in food products. Although some may think these non-animal substitutes are only products developed to cater needs of a small group of consumers, the plant-based industry can also be viewed as one of the moral markets (Vedula et al., 2022), the development of which aligns with broader concerns

[11] Plant-based protein belongs to an overarching family of "alternative protein", referring to alternative protein sources used in the food production process to replace animal protein that is derived conventionally (i.e. from animal agriculture, commercial fishing etc.). Apart from plant-based, other technologies under development include cell-based, fermentation-derived, as well as insects-based. Plant-based products are by far the largest and most developed technology in the alternative protein family. Since most plants and ingredients are already established to be edible by humans, most plant-based products don't involve a regulatory process by authorities, in order to go into market. Given that other technologies are still under development with few commercialization successes, we do not consider these technologies in this research.

about climate change, sustainability and animal welfare. According to Food and Agriculture Organization of the United Nations, the conventional food production accounts for 26% of global greenhouse gas emissions, 50% of global habitable land use and 70% of freshwater use (FAO, 2011). Animal-related products take up the majority of these environmental impacts, yet are proven to be inefficient in providing humans with needed nutrition. For example, raising animals and growing crops to feed animals take up about 77% of global farming land, while they produce only 18% of total calories and 37% of proteins (Poore & Nemecek, 2018). Hence, in order to feed a growing population that is projected to reach 10 billion by 2050, it becomes crucial to develop new products or production methods to replace conventional animal-based products.

Depending on the time of development and its technical complexity, plant-based products can be categorized into two broad types: novel and traditional (also often referred to as vegetarian/vegan food, before the term ‘plant-based’ became more rampant). Both types of products exist in the current market and have differing impacts on industry dynamics.

Traditional veggie foods are made of soy, mushroom, or jackfruit. The production process mostly involves form pressuring and requires minimal processing of the input materials. Targeting only a niche market of vegetarian and vegan consumers, these products are not appealing to the mainstream market in terms of their taste profile. Several leading veggie food producers, such as Tofurky, Oatly, Lightlife, were founded in the 1970s to 1990s. Before 2010s, the dynamics of the broader food and beverage industry resembled what organizational ecology researchers theorize about a stable dual market structure resulting from resource partitioning, where generalists and specialists depend on different resource spaces and do not compete directly (Carroll, Dobrev, & Swaminathan, 2002). Established food manufacturers and conglomerates are generalists that occupy the mainstream market and have a history and tradition in manufacturing dairy and meat products, whereas veggie food producers are specialists who serve vegetarian and vegan consumers and produce animal-free foods solely.

This stable dual market structure begins to change around 2010s when novel plant-based food products start to emerge. These products are initiated by some food-tech startups, such as Beyond Meat (founded in 2009), Impossible Foods (founded in 2011), that started to use various mechanical (e.g., 3D printing) and chemical approaches (e.g., biomimicry) to produce products that resemble conventional meat products in their sensory profiles. In addition, a larger variety of crops, such as pea, oat, potato etc., are used and optimized to extract the analogous components in meat, that is, protein, fat, vitamins, minerals, and water. In addition to meat and dairy products, plant-based products are also expanding in other categories, such as eggs and seafood. The target is not merely to capture a small segment of peripheral vegetarian and vegan consumers but to appeal to mainstream omnivore consumers.

The rise of plant-based industry blurred the market boundary that is used to differentiate generalist and specialist food producers. During the last decade, the industry becomes turbulent with a lot of entry and exits. Plant-based food startups have received endorsements from influential investors such as Google Ventures (GV), Temasek Holdings, and Bill Gates, who deemed meat substitute as the future of food and an important way to tackle climate change (Gates, 2013, 2021). A highlight is when the VC-backed startup Beyond Meat made its initial public offering, experiencing a remarkable 163% rise and becoming the biggest-popping IPO in the US since 2000 (Murphy, 2019). Our study on entrepreneurial activities in this industry will focus on this period where dramatic increases of both entry and investor investments are observed. The next section will describe these trends in detail.

3.4 Data and Methodology

3.4.1 Sample

Entry data. We began by drawing a sample of global firms producing plant-based end products for consumers ($N = 1{,}195$) from the alternative protein company database of the Good Food Institute (GFI)[12]. In order to assess the representativeness of companies listed in the dataset, we corresponded with GFI about their sampling criteria. The dataset lists companies that have direct involvement in the alternative protein industry through a (planned) product line on the market. Both companies whose primary focus is alternative protein as well as those who have light involvement in the industry are included. The majority of companies are compiled internally, from sources such as trade show lists, startup databases like Crunchbase and Pitchbook, and news articles featuring companies. Some companies also submit their own information if they are not included. According to GFI, this is the most comprehensive list of global companies in the alternative protein industry. Apart from company name, GFI's company dataset provides demographic information including founding year, country of incorporation, name of founders, company website, protein category (e.g., plant-based, cultivated, fermentation etc.), and product focus (e.g., meat, seafood, dairy, eggs).

Since we are interested in entrepreneurial activities in this industry, we verified each company from GFI's list manually, and eliminated the following types of companies from the sample: 1) Companies that do not primarily focus on plant-based products, these include some conglomerates (e.g., Coca-Cola), meat and dairy industry incumbents (e.g., Tyson Foods, a major meat processor), retailers that introduce a line of plant-based products (e.g., Carrefour); and some diversifying entrants (e.g., Riso Scotti, an Italian rice producer that adds rice-based milk in its product lines); 2) Companies that do not provide products directly to end consumers, these include B2B and ingredient companies (e.g., NewFields, a wholesaler), and

[12] The Good Food Institute is a nonprofit organization that aims to support and accelerate the alternative protein industry. The company database is obtained at the beginning of 2023.

biotechnology firms that supply proteins (e.g., Kyomei Proteins); 3) Companies that do not focus on products for human consumption, for instance plant-based pet food producers (e.g., Petaluma). We also aggregated brands that belong to the same company, and dropped companies that are founded after 2022. This step left us with 913 unique companies that have a primary focus in the plant-based category.

Financing Data. We searched and obtained each company's financing history and exit events primarily from Pitchbook, a novel and fast-evolving dataset that is reported to have better coverage and provide more accurate funding information (Retterath & Braun, 2020). Pitchbook includes companies that have received at least 10,000 USD from any type of investor. If a company is not present in Pitchbook, we further checked it in two other entrepreneurial financing datasets: Crunchbase and in CBinsights. Companies that are not present in either of these three databases are coded as not receiving any financing. For startups that have received financing, we further obtained information on deal date, type of deal, and investor type etc.

Website Data. To study the evolution of startups' strategies of rhetorical framing using various institutional logics, we scraped each company's historical website using Wayback Machine[13], a digital library of archived webpages provided by the Internet Archive. Starting from 1996, the Wayback Machine crawled and archived web pages from the Internet at irregular intervals (several times a year) and contains 735 billion web pages (Internet Archive, 2023). For the second part of our study, we obtained a screenshot of each company's website every year, starting from a company's founding year till 2022. Specifically, the screenshot of a web page that is closest to Dec. 31st of a respective year is downloaded. We follow Guzman & Li (2023) and limit the contents to the homepage and only the first-level links *(up to 10 URLs for each company per year)*. Empty pages, pages with too little texts (fewer than 50

[13] https://web.archive.org

characters), pages that return HTTP errors, as well as boilerplates (e.g., GoDaddy) are considered invalid and discarded.

For this part of our analysis, we had to eliminate 15 companies that do not have a valid webpage, as well as companies that only use social media platforms (such as Instagram, Facebook, or LinkedIn) as their homepage. For webpages that are successfully loaded, we used the python package "langdetect" to determine the language of the webpage. Given that automated text analysis tools demonstrate higher accuracy and consistency with English texts, we excluded websites from 285 companies whose websites are not in English.

3.4.2 Measures

Table 3.1 summarizes variable names and dentitions for the two parts of our analysis respectively. For hypotheses 1 and 2, our dependent variable is new entry. In line with previous research, our dependent variable *Entry* is measured as the annual count of newly founded plant-based companies in a country. As we show below, entry pattern and investment activities may also vary among the four protein categories: meat, dairy, egg, and seafood. Hence, we refined our observation at the country-protein-year level. Our main independent variable, *VC-Plant,* is a proxy for the overall interests from venture capitalists in this nascent industry. Previous research either uses the count of VC deals or the aggregate amount of investment value as a proxy for VC activities (e.g., Popov & Roosenboom, 2013; Samila & Sorenson, 2011). We chose not to rely on investment size as a proxy, since 27.5% of deals in our sample did not disclose their deal size. Hence, similar to the entry variable, *VC-Plant* measures the annual number of plant-based deals from professional venture capitalists in a given country in a protein category. Given the probable time lag for the impact of VC interests on entry decisions to manifest, we follow prior practices by constructing both a one-year lag of the variable as well as a rolling two-year investment average.

Our second hypothesis predicts that a shift in investors' focus towards engaging in more follow-on deals will likely dampen the positive effect of venture capital interests on market entry. For this purpose, we created a dummy variable *Follow-on Focus* indicating the observations when the number of follow-on VC deals exceed first-time VC deals in a country in a protein category. We further included several control variables at various levels of observation. Research in organizational ecology (e.g., Carroll, Dobrev, & Swaminathan, 2002) shows that the founding of new firms is dependent upon industry population density, incorporating both an early-stage legitimacy mechanism and a later-stage competition mechanism. For this purpose, we created *Density*, representing the total number of plant-based companies operating in a country in a specific protein category in a given year, and included its squared term in our analysis. In addition, we introduced two country-year level control variables. Acknowledging that VC interests in this industry may be influenced by the broader availability of venture capital, *VC-Country* measures the annual number of VC deals in a country. This measure serves to capture the overall volatility and trends in VC investments at the national level. Further, we included country-year level *Population* data as a control for the overarching demand for plant-based products.

Table 3.1 Summary of Variables

Variable	Definition	Unit of Observation
Panel A: Entry		
Entry	Annual number of plant-based startups founded in a country in a protein category	Country-protein-year
VC-Plant	Annual number of plant-based VC deals in a country in a protein category 1) VC-Plant_L1: lag by one year 2) VC-Plant_M2: rolling two-year average	Country-protein-year
Follow-on Focus	Dummy = 1 if annual number of follow-on deals exceed annual number of first-time deals in a country in a protein category	Country-protein-year
Density	Total number of plant-based companies in a country in a protein category in a given year	Country-protein-year
VC-Country	Annual number of VC deals in a country	Country-year
Population	Total number of populations in a country in a given year	Country-year
Panel B: Institutional Logics		
VC-backed	Dummy = 1 for the deal year and subsequent years when a company receives its first time VC investment Lead and lags created for 5 years prior to and 5 years after respective first VC year	Company-year
Number of institutional logics	The count of institutional logics in a company's website in a given year. Value range: [0,3], where 0 indicates no presence of any logics and 3 indicates presence of all three logics	Company-year
Country	Startup's country of incorporation	Company
Protein Focus	Categorical variable that indicates a startup's primary focus in the four protein categories: meat, dairy, egg, seafood	Company

Table 3.1 Panel B lists the main variables included for our third hypothesis. The independent variable *VC-backed* is a binary variable. It is equal to 1 once a startup receives its first time VC deal, and 0 otherwise (i.e. for the years prior to VC deal and for all years of non-VC-backed startups). As detailed in the next section, we also created for regression analysis leads and lags for VC-backed startups five years prior to and five years after first-time VC

investment. The dependent variable is the number of institutional logics observed at startup-year level. In the following, we describe the process of how we measure this variable from startups' historical websites.

Preprocessing website texts. Preprocessing text data is important to enhance measurement precision (a recent discussion of preprocessing texts see Hickman, Thapa, Tay, Cao, & Srinivasan, 2022). For the purpose of our study, we begin with tokenization and create a list of words for each document (website text per firm per year). We transformed each word to lowercase, and then apply lemmatization so that all functional variations are reduced to the base form. For example, instead of treating all conjugated verb forms of "ate", "eaten", "eating" as unique words, they will all be changed to the original form "eat". Since we are interested in "what" startups communicate, rather than "how", we kept only content words (nouns, verbs, adjectives, adverbs, and proper names) and removed all function words (e.g., articles, auxiliary verbs, conjunctions, prepositions, and pronouns), the use of which is more important to identify speech styles rather than contents (Hickman et al., 2022). Lastly, we removed special characters (e.g., "™", "©", "®") and typical words related to website that are not meaningful to our research (e.g., "cookie", "privacy", "policy", "terms", "conditions"). After preprocessing, the average document length is reduced from 13111 to 1156 words.

Measuring the number of logics. We used a dictionary-based approach to study the use of institutional logics within the industry. Through qualitative examination of media outlets (e.g., The Economist, 2019, 2022), reports from mission organizations advocating for this industry (e.g., GFI annual reports), as well as the historical websites of startups[14], we identified three primary logics prevalent in this industry: animal welfare, health, and environmental sustainability. Subsequently, we compiled a list of keywords (Table 3.2) for each of the three logics. These keywords were then cross-referenced with startups' website texts. Detection of a

[14] We show example website excerpts in the next section.

match with any keyword signified the presence of a specific logic in a startup for a given year. We then aggregated the count of logics at startup-year level.

Table 3.2 Keywords for Identifying Institutional Logics

Logics	Keywords
Animal	animal, welfare, wildlife, ethical, cow, farming
Health	well-being, health, nutrition, disease, fitness, wellness, healing
Sustainability	Earth, planet, environment, sustainable, climate, biodiversity, greenhouse, pollution

3.5 Results

3.5.1 Entry

3.5.1.1 Descriptive Trends: Entry and investment activities

Entry pattern. We first present a comprehensive overview of aggregated entry and investment activities within the entire plant-based industry, organized by country and by year. Plant-based companies have been established in 56 countries globally. Table 3.3 below lists the top 15 countries with more than 10 plant-based companies. The United States leads with the highest number of plant-based companies (n = 275), followed by United Kingdom (n = 76), Germany (n = 52), India (n = 50), and Canada (n = 43). Interestingly, apart from India where the vegetarian population constitutes the highest percentage (approximately 20-30%), the countries with the most plant-based entrants are not the ones with highest percentage of vegetarians.

Table 3.3 Number of Entries by Country

Countries (with 10 or more plant-based companies)	No. of entry Before 2008	No. of entry After 2008	Total	%
United States	38	237	275	30.12
United Kingdom	14	62	76	8.32
Germany	12	40	52	5.70
India	1	49	50	5.48
Canada	7	36	43	4.71
Brazil	5	35	40	4.38
France	6	31	37	4.05
Netherlands	3	28	31	3.40
Spain	6	22	28	3.07
Israel	1	25	26	2.85
Singapore	5	18	23	2.52
Sweden	4	16	20	2.19
China	2	16	18	1.97
Italy	7	11	18	1.97
Australia	1	15	16	1.75
Russia	1	9	10	1.10
Sub-total	117	646	763	83.57
Other Countries (with less than 10 plant-based companies)	22	128	150	16.43
Total	139 (15.22%)	774 (84.78%)	913	100

Among the 913 companies operating in this sector, 774 (84.78%) were established post-2008. Figure 3.1 further plots the number of new entrants in the United States, Europe, and rest of the world respectively, each hosting about one third of the total entrants. Before 2008, the industry is relatively dormant with negligible changes in entries. Subsequently, a noticeable increase in entry activity becomes apparent, gaining momentum around 2013-2014. The number of entry peaks in 2019 for the United States and in 2020 for Europe and the rest of world. The following years witness a sharp decline in entry.

Figure 3.1 Number of New Entries by Region

Figure 3.2 illustrates the number of entries categorized by protein focus[15]. Predominantly, meat substitutes and dairy alternatives emerge as the two primary product types with the highest influx of new entrants. Notably, the dairy alternative category led in entries until 2018, after which startups focusing on meat substitutes surpassed this trend. Concurrently, startups specializing in seafood and egg-related products depict a subtle and incremental rise over the years, persisting up to 2021.

[15] About 17% of the startups have focus in more than one protein type.

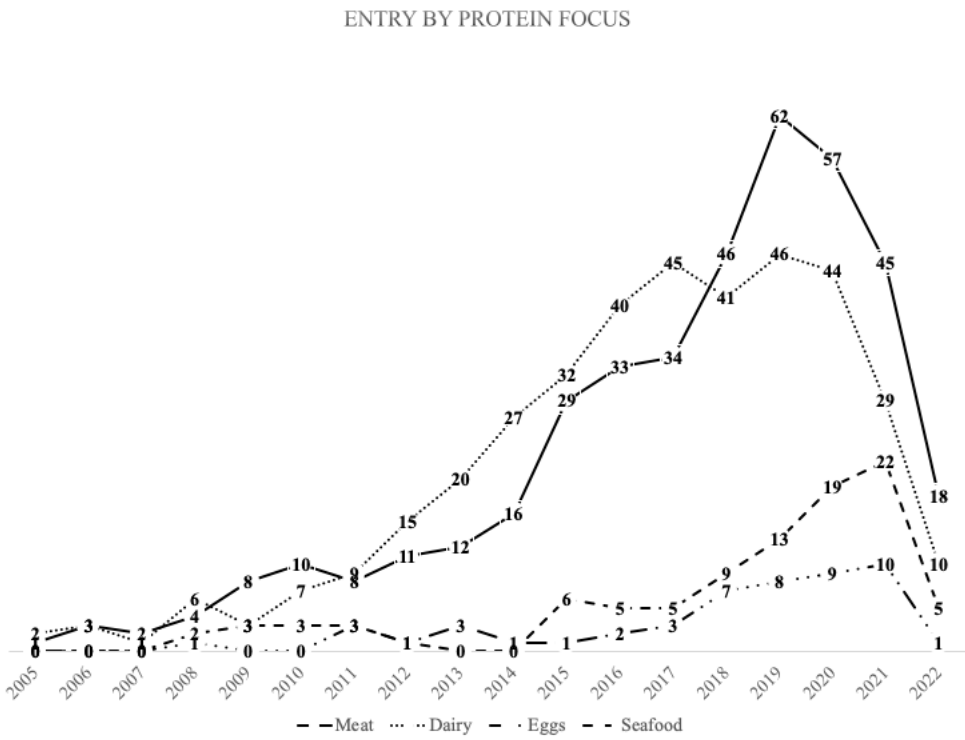

Figure 3.2 Number of New Entries by Protein Focus

Investment activities. We have identified a total of 995 financing deals for our sample startups[16]. These include investments from professional venture capitalists (62.51%), as well as deals from accelerator and incubator programs (20%), investments from individual angel investors (7.44%), product and equity crowdfunding (5.63%), and grants (4.42%). Focusing only on deals from professional venture capitalists, Figure 3.3 illustrates the total investment amount and number of VC deals in the industry by deal year. There is a steady increase both in deal count and size persisting to 2021. The total investments amount to 7.8 billion USD in this industry[17].

When examining the percentage of equity-financed companies in this nascent industry, approximately 40% have secured some form of funding, 32% if we exclude unprofessional investors and only consider investments from venture capitalists. This percentage is incredibly

[16] We did not include any private equity deals that primarily target mature companies. 24 companies in our sample received growth capital or PE investments without prior funding from VC or other unprofessional investors.

[17] The overall funding amount is likely to be higher, given that 27.5% of deals in our sample did not disclose their deal size.

high, suggesting that a new startup in this industry stands a one-in-three chance of receiving funding from a venture capital investor. This is consistent with numerous media reports highlighting a substantial interest in this sector from venture capitalists, celebrities, and notable figures such as Bill Gates. It is noteworthy that the majority of these VC-backed ventures (approximately 85%) were also established after 2008.

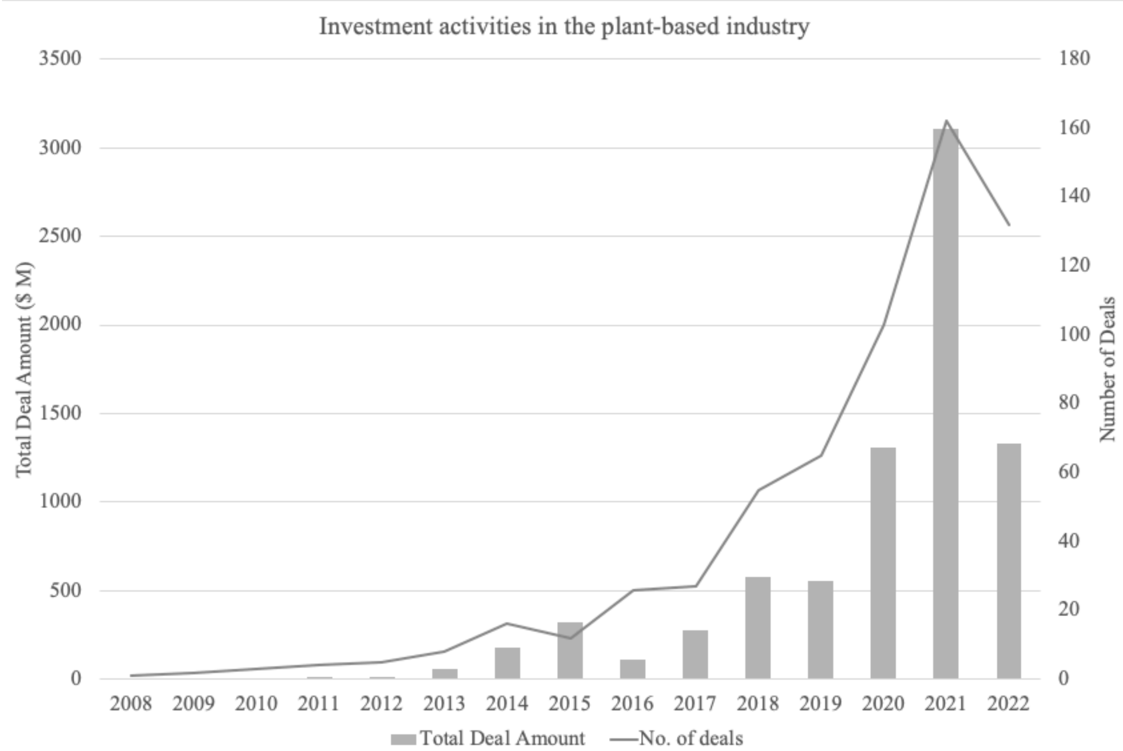

Figure 3.3 Investment activities in the plant-based industry

Figure 3.4 plots the number of new startups as well as the number of first and follow-on VC deals in the industry from 2008 until 2022. The funding of plant-based companies started in 2008[18], followed by a consistent rise in both first-time VC deals and follow-on deals, persisting up to 2021. Notably, the percentage of follow-on deals exceeded that of first-time VC deals starting in 2019, coinciding with the year in which the number of new entrants in the industry reached its plateau and began exhibiting initial signs of decrease.

[18] We only identified one single deal (in 1997) occurring prior to 2008.

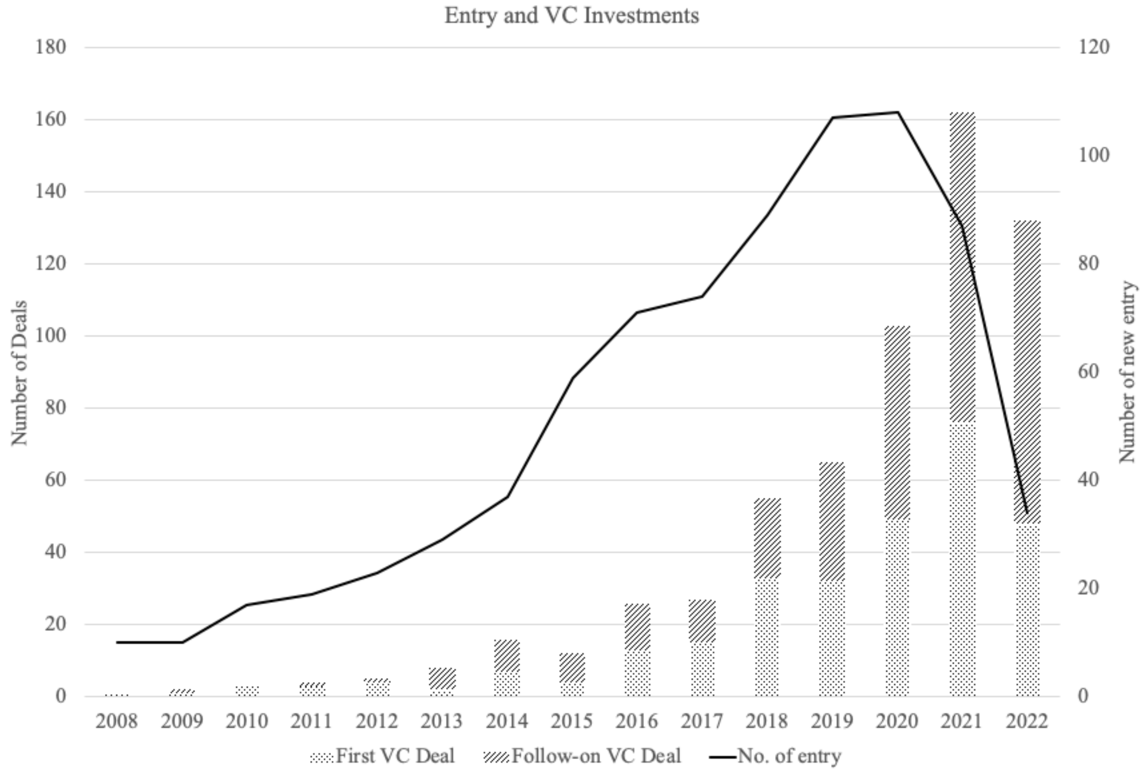

Figure 3.4 Entry and VC investments in the plant-based industry

3.5.1.2 Regression analysis: Entry

As mentioned in the earlier section, our unit of observation is at country-protein-year level. Since we only observed investment activities from 2008 onwards, we restrict our regression analysis to observations between 2008 and 2022. To eliminate concerns that some countries only observe one-time entry per year, we restrict our analysis to the 15 countries with more than 10 plant-based companies as listed in Table 3.3. This results in a balanced sample of 960 observations.

Table 3.4 Panel A1 presents descriptive statistics at country-protein-year and country-year level respectively. All the variables show a substantial variation. Averaging across all countries, protein categories, and years, the annual number of entries in a protein category in a country is 0.8, while the annual number of deals 0.67. It is worth mentioning that our data are over-dispersed, with 66.15% observations having zero entries at country-protein-year level.

Table 3.4 Summary Statistics

Panel A1: Entry (Country-Protein-Year Level)					
Variable	Obs.	Mean	Std. Dev.	Min	Max
Entry	960	.797	1.877	0	22
VC-Plant	960	.673	2.576	0	35
VC-Plant (Two-year average)	960	.668	2.264	0	30.5
First VC Deal	960	.304	1.061	0	12
Follow-on VC Deal	960	.369	1.653	0	25
VC-Country	960	2060.675	4286.477	19	26692
Density	960	6.946	14.878	0	138
Population (in mil.)	960	236.501	428.356	4.839	1417.173
Follow-on Focus	960	.092	.289	0	1
Panel A2: Entry (Country-Year Level)					
Variable	Obs.	Mean	Std. Dev.	Min	Max
Entry	240	3.188	5.536	0	47
VC-Plant	240	2.692	8.049	0	71
VC-Plant (Two-year average)	240	2.562	7.407	0	66.5
First VC Deal	240	1.217	3.126	0	23
Follow-on VC Deal	240	1.475	5.187	0	48
VC-Country	240	2060.675	4293.197	19	26692
Density	240	27.783	44.846	1	318
Population (in mil.)	240	236.501	429.028	4.839	1417.173
Follow-on Focus	240	.167	.373	0	1
Panel B: Institutional Logics (Company-Year Level)					
Variable	Obs.	Mean	Std. Dev.	Min	Max
Number of logics	3157	1.958	.923	0	3
VC-backed	3157	.232	.422	0	1
Logic of health	3157	.945	.229	0	1
Logic of animal	3157	.418	.493	0	1
Logic of sustainability	3157	.595	.491	0	1

We used a fixed-effect Poisson regression (Wooldridge, 1999) to estimate the effect of VC activities on entry. We opted for the Poisson model over negative binomial models, as prior research suggests that the conditional negative binomial model for panel data is not a true fixed-effects method (Allison & Waterman, 2002). Additionally, it does not offer an advantage in dealing with overdispersion. In the regression analysis, we applied a logarithmic transformation to the total number of VC deals in a country, as well as to the density and population variable. For the density variable, we added one to all observations before the log-transformation. Table 3.5 below presents the results. All models use a fixed-effect Poisson estimate with error clustering at country-protein category level. In Models 1-3, we use a one-year lag of VC Deals in the plant-based industry as predictor. Model 1 is a univariate regression showing strong positive effect of VC interests on the number of new entries. In Model 2, we included all control variables and year dummies, which leads to a substantial increase in the log-likelihood function, suggesting a better model fit. The main independent variable remains significant and positive. We also observed a significant negative effect of the squared *Density* variable, indicating an effect of market saturation and increased competition. In model 3 we added the interaction term between overall VC interests and a shift of focus towards follow-on deals. Adding the interaction term increases the magnitude of effect of the main predictor VC interests. Moreover, we observe a significant negative interaction effect, suggesting that the effect of VC interests on entry is attenuated in observations when follow-on deals are dominant. We replicated these analyses using two-year average VC deal as predictor in Models 4-6. The results remain robust with greater magnitude. Taken together, these results strongly support our first two hypotheses.

Table 3.5 Country-protein-year Level Poisson Regression

VARIABLES	(1) Entry	(2) Entry	(3) Entry	(4) Entry	(5) Entry	(6) Entry
VC-Plant$_{(t-1)}$	0.02***	0.03*	0.05**			
	(0.00)	(0.02)	(0.02)			
Follow-on Focus$_{(t-1)}$			0.04			0.15
			(0.19)			(0.20)
VC-Plant$_{(t-1)}$ × Follow-on			-0.03**			
Focus$_{(t-1)}$			(0.01)			
VC-Plant $_{\text{(two-year average)}}$				0.03***	0.00	0.07*
				(0.01)	(0.03)	(0.04)
VC-Plant $_{\text{(two-year average)}}$ ×						-0.06***
Follow-on Focus$_{(t-1)}$						(0.02)
Ln (VC-Country) $_{(t-1)}$		0.37	0.42		0.34	0.45
		(0.31)	(0.30)		(0.31)	(0.29)
Ln (Density) $_{(t-1)}$		-0.15	-0.22		-0.32	-0.24
		(0.34)	(0.34)		(0.35)	(0.35)
Ln (Density) $_{(t-1)}$ - Squared		-0.20***	-0.19***		-0.15*	-0.19**
		(0.06)	(0.06)		(0.08)	(0.08)
Ln (Population) $_{(t-1)}$		6.45	6.23		6.88	6.05
		(6.16)	(6.07)		(6.15)	(6.05)
Observations	826	826	826	885	826	826
Log-likelihood	-782.4	-606.9	-604.3	-828.5	-608.3	-603.0
Country-Protein Cluster FE	YES	YES	YES	YES	YES	YES
Year Dummies		YES	YES		YES	YES

Note: 5 groups (70 obs.) are dropped because of all zero outcomes.
Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

We report further in Table 3.6 re-estimation of data aggregated at country-year level. This aggregation results in a relatively small sample, with 240 observations across 15 countries. Overall, the main results are similar to analyses at country-protein-year level. In the full models 3 and 6, we observed both a significant positive effect of *Density* and a negative effect of the squared *Density* term, indicating the presence of both legitimation and competition effects. These effects are consistent with the research findings from population ecology.

Table 3.6 Country-year Level Poisson Regression

VARIABLES	(1) Entry	(2) Entry	(3) Entry	(4) Entry	(5) Entry	(6) Entry
	(0.00)	(0.01)	(0.02)			
Follow-on Focus$_{(t-1)}$			0.07			0.16
			(0.20)			(0.22)
VC-Plant$_{(t-1)}$ × Follow-on Focus$_{(t-1)}$			-0.02***			
			(0.01)			
VC-Plant $_{\text{(two-year average)}}$				0.01***	0.01	0.04**
				(0.00)	(0.01)	(0.02)
VC-Plant $_{\text{(two-year average)}}$ × Follow-on Focus$_{(t-1)}$						-0.03***
						(0.01)
Ln (VC-Country) $_{(t-1)}$		0.51	0.62		0.50	0.64
		(0.60)	(0.58)		(0.59)	(0.57)
Ln (Density) $_{(t-1)}$		1.00	1.13*		0.90	1.23*
		(0.71)	(0.63)		(0.73)	(0.67)
Ln (Density) $_{(t-1)}$ - Squared		-0.22**	-0.25**		-0.20	-0.27**
		(0.11)	(0.10)		(0.13)	(0.12)
Ln (Population) $_{(t-1)}$		3.18	2.63		3.43	2.24
		(5.01)	(5.14)		(5.04)	(5.21)
Observations	224	224	224	240	224	224
Log-likelihood	-512.6	-348.6	-343.3	-546.9	-349.4	-342.5
Country FE	YES	YES	YES	YES	YES	YES
Year Dummies		YES	YES		YES	YES

Robust standard errors in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

3.5.2 Institutional logics

3.5.2.1 Descriptive Statistics: The evolution of institutional logics

We start with some qualitative observations about how startups frame their products on websites over time. Table 3.7 below shows example text excerpts from the historical homepage of two pioneering plant-based startups in the past decade: Beyond Meat and Impossible Foods[19]. It is apparent that both companies rely on value-loaded institutional logics to frame their innovative offerings. While Impossible Foods consistently emphasizes the environmental and health-related aspects of their products, Beyond Meat takes a multifaceted approach by

[19] Beyond Meat was founded in 2009 and marked its first product launch in 2012. Impossible Foods was established in 2011, and introduced its first product in 2016. Both companies have garnered substantial support from venture capital. Beyond Meat raised approximately $122 million in funding before going public in 2019, while Impossible Foods raised over $2 billion and remained private to date.

highlighting not only environmental and health factors but also emphasize animal welfare and, in later communications, community-related aspects. Another interesting observation from our qualitative analysis of the homepage of these two companies is the absence of any mention of the terms “vegan” or “vegetarian”, the traditional category that persists in this industry. As pioneering startups with innovative food technologies, both companies consistently underscore the novel terms “plant”, “plant-based”, “plant protein” when describing their products.

Table 3.7 Excerpts from the Homepage of Two Pioneer Plant-based Companies

Year	**Beyond Meat**	**Impossible Foods**
2014	At Beyond Meat, our vision is 25/20. 25% reduced global meat consumption by 2020. “Made from plants, tastes like freedom”	You love meat. You love cheese. For thousands of years we've relied on animals to make them. Impossible Foods has found a better way. We use plants to make the best meats and cheeses you’ll ever eat.
2015	Meat is actually pretty simple: amino acids, fats, carbohydrates, trace minerals and water combined to give us that familiar chew, resistance, and variation. But what if we are able to take these same inputs from plants and combine them to look and feel just like animal meat? What you’d have is meat for the future.	Impossible Foods is developing a new generation of delicious and sustainable meats and cheeses made entirely from plants. Our mission is to give people the enjoyment of food that comes from animals without the health and environmental drawbacks.
2016	We hope our plant-based meats allow you and your family to eat more, not less, of the traditional dishes you love, while feeling great about the health, sustainability, and animal welfare benefits of plant protein.	The world loves meat. But relying on cows to make meat is land-hungry, water-thirsty, and pollution-heavy. That’s why we set out to do the impossible: make delicious meats that are good for people and the planet.
2017	Removing the animal from the protein production chain simultaneously and powerfully addresses four major problems attributable to livestock. Improving human health Positively impacting climate change Addressing global resource constraints Improving animal welfare	Every time you choose a quarter-pound Impossible Burger instead of a burger made from a cow, you can make a huge difference without compromising. You spare 75 square feet of land for wildlife. You save water equivalent to a 10-minute shower. You spare 17 driving miles-worth of greenhouse gases.
2018	... The study concluded that The Beyond Burger uses significantly less water, less land, generates fewer Greenhouse Gas Emissions (GHGE), and requires less energy than a beef burger.	We make delicious meat from plants. All the mouthwatering flavor – with a tiny fraction of the environmental impact of meat from cows.
2019	We hope our plant-based meats allow you and your family to eat more, not less, of the traditional dishes you love, while feeling great about the health, sustainability, and animal welfare benefits of plant protein.	Why make meat from plants? For all the mouthwatering flavor and only a tiny fraction of the environmental impact of meat from cows. Eat up. Save Earth.
2020	Go beyond. The positive choices we make can have a great impact.	… our progress toward a more sustainable food system. … we focused on our growing social good program, our zero waste journey, how to turn back the clock on climate change and halt biodiversity collapse, and much more.
2021	Our mission is to create delicious, nutritious, sustainable protein so that you can Eat What You Love™, no sacrifice required. Meat that’s better: For you. The planet. Your taste buds.	By eating meat made from plants instead of meat made from animals, we can drastically cut our carbon footprint, save water supplies and help ensure that our precious Earth is here not just tomorrow but for future generations. With Impossible Burger, it’s never been more delicious to save the planet.
2022	We have the support. The people, places and communities that Go Beyond their own limits.	Heart-check certified by the American heart association. Diets low in saturated fat and cholesterol, and as low as possible in trans fat, may reduce the risk of heart disease.

We next set out to understand what are some common themes across companies' websites in this industry. Figure 3.5 below shows a word cloud based on key phrase frequency when we aggregate all website texts across firms and years. The most frequent terms are predictably terms that depict the nature of the products: “dairy free”, “plant base”, “vegan cheese”, “veggie burger”, and “meat alternative”. Another salient feature is the common commerce-related logic, with phrases such as “store locator”, “add cart”, “free shipping” indicating that these startups primarily communicate through their website, offering information on where to find their products or facilitating direct online sales. In addition, a recurrent theme is associated with the health logic, evident in phrases like “health benefit”, “health food” and “natural food” emphasizing the perceived health-related attributes of their offerings.

Figure 3.5 Word Cloud Illustration Based on Term Frequency

In the following, we compared term frequencies of the traditional and novel category 'vegan' vs. 'plant-based'[20]) in VC-backed and non-VC-backed companies. For this purpose, we use a bag-of-words representation, i.e. we create a count vector for each unique word in the website texts and count for each document how often the word appears. Figure 3.6 below illustrates the average term frequency of both categories by company between 2009 and 2022. We observe a growing prevalence of the novel category 'plant-based' across all firms,

[20] We aggregated 'vegan', 'vegetarian', 'veggie' to the category 'vegan'. Similarly, we aggregated 'plant', 'plant-based', 'plant based' to the category 'plant-based'.

indicating its increasing dominance in this industry. As of 2022, the terms ‘plant-based’ and ‘vegan’ show equal frequency in the websites of VC-backed companies. In contrast, non-VC-backed companies use the term ‘vegan’ twice as often as ‘plant-based’. This might suggest a divergent competitive positioning between VC- and non-VC-backed companies. The transition in category usage not only signifies the strategic move by novel foodtech startups to differentiate themselves from traditional specialist producers based on their advanced technology but also serves as a deliberate strategy to appeal to a wider range of consumers. The term ‘vegan’ can sometimes carry exclusive connotations, akin to a membership card for a selective club, potentially alienating mainstream consumers (Ramanathan, 2019). On the contrary, the term ‘plant-based’ is more inclusive, not requiring consumers to have a vegetarian/vegan identity, making it easier for these products to be incorporated into their existing eating habits.

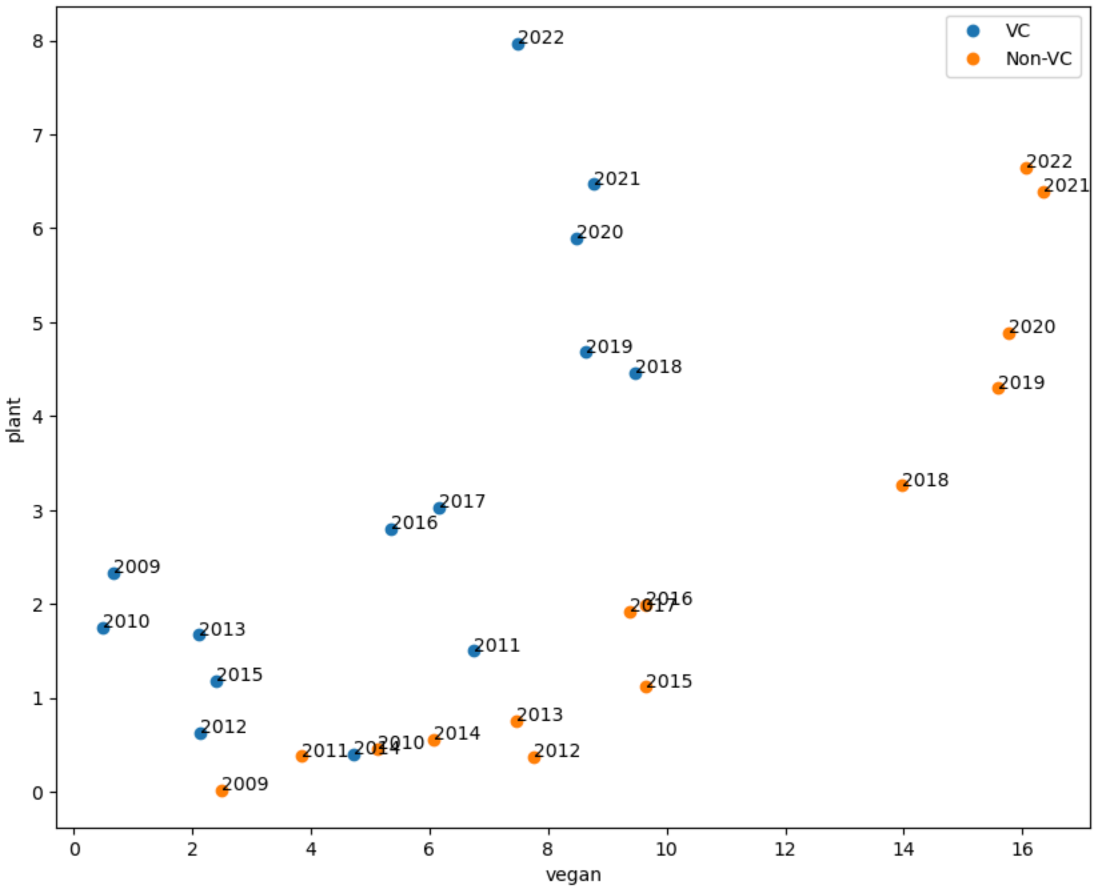

Figure 3.6 Term Frequency (‘plant-based’ vs. ‘vegan’) in VC- & non-VC-backed Companies

3.5.2.2 Regression analysis: The number of institutional logics

In the regression analysis, our aim is to study whether startups, subsequent to receiving VC investments, are inclined to incorporate a higher number of institutional logics in their product framings in comparison to their counterparts that do not receive VC financing. Given that the year of first VC financing is different across startups, we employ a panel event study (Clark & Schythe, 2021), which allows us to create time-to-event dynamic leads and lags to a startup's respective VC year. Startups that never received VC financing (event never occurred) are treated as counterfactuals. We regressed on the number of institutional logics and incorporated firm-level fixed effects to control for unobserved heterogeneity at the firm level.

Figure 3.7 plots the point estimates of the use of number of institutional logics at 90% confidence interval. Prior to the event of VC financing, there is no significance difference across startups in the number of institutional logics used, which indicates a "parallel trend" in this baseline period. After the event of VC-financing, in particular starting from t+1, there is a growing positive difference in the number of institutional logics used over time. This suggests that startups use a higher number of logics after receiving VC investments when framing their products on their websites, providing support to our third hypothesis. In line with our arguments, this finding indicates that venture capitalists might influence startups' product positioning by prompting them to use more value-laden logics, aiming for a broader appeal and acceptance among various segments of consumers.

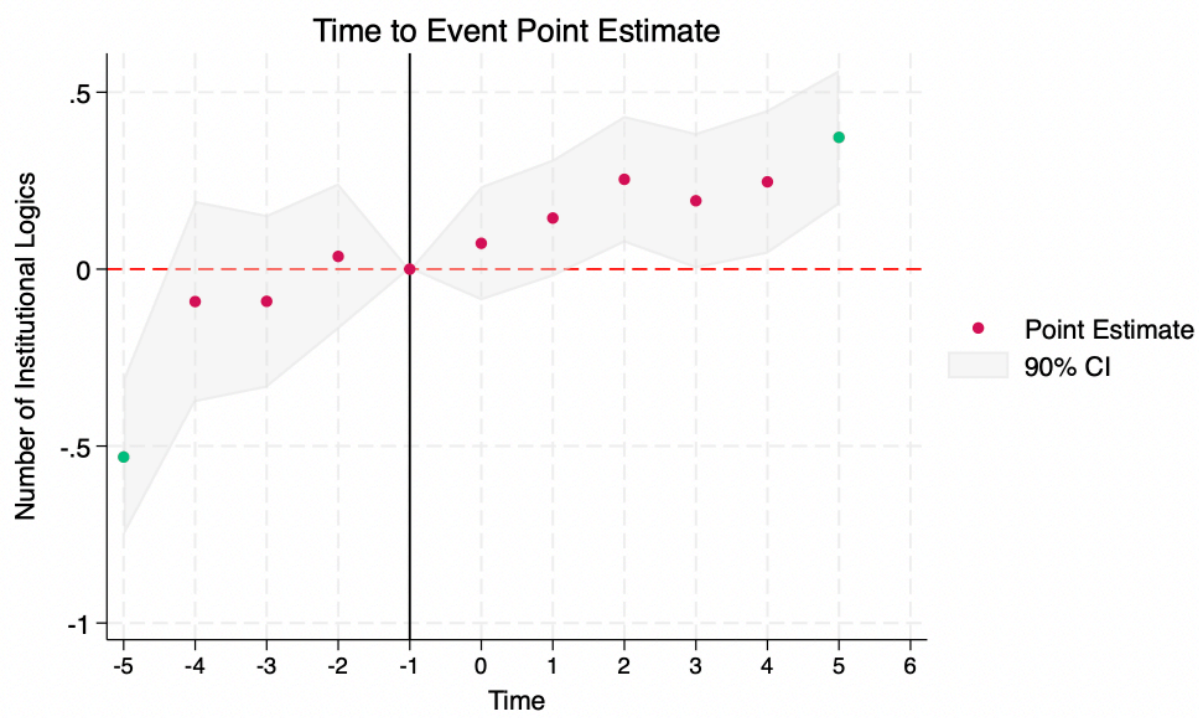

Figure 3.7 Point Estimate of Panel Event Study

3.6 Discussion

This study explores the role of venture capital in shaping entrepreneurial activities in a nascent industry. We compiled a unique panel dataset of startups entering the nascent plant-based industry with matching funding history and historical website text data. Our analysis shows that VC interests positively affects entry. With the expansion of the nascent industry, this effect is diminished when the number of follow-on deals exceeds that of initial investments. In addition, we show that following VC investments, startups are more likely to use a higher number of institutional logics in their website, suggesting a broader product market positioning.

We contribute to the extant literature in several ways. First, prior literature generally establishes that VC interests promote entry at regional and country-level (Mollica & Zingales, 2007; Samila & Sorenson, 2011; Popov & Roosenboom, 2013). Our study provides a more nuanced framework, delineating the conditions under which venture capital activities induce or even deter entry. In this regard, our study provides empirical evidences showing that apart from product-market channels, entry deterrence may take place through financial channels (Cestone & White, 2003).

Second, we propose an alternative mechanism about how VCs help portfolio companies in attaining superior product market outcomes. Existing research suggest that a higher increase in sales by VC-backed startups can be attributed to a better-quality workforce (Chemmanur et al., 2011). For example, Hellmann & Puri (2002) found that VC-backed startups are faster to hire a VP of marketing. In addition, portfolio companies may benefit by accessing VC investors' network of contacts (Hochberg et al., 2007), including suppliers and potential customers. Our findings suggest that VCs help portfolio companies navigate the complex institutional environment in a nascent industry. By encouraging a broader market positioning and the integrate of multiple institutional logics, VCs actively contribute to expanding the niche focus of a nascent industry.

Third, we contribute to the entrepreneurship literature (Davidsson, 2015; Shane, 2012) by underscoring the essential role played by VC in the entrepreneurial ecosystem. As "External Enablers", the evolving nature of VCs' investment strategies influence entrepreneurs' formation of "New Venture Ideas" and the perception of "Opportunity Confidence" over time. Furthermore, VCs actively contribute to shaping the strategies of entrepreneurial startups, playing a pivotal role in fostering their growth.

Future work could extend our research in several ways. To begin with, our study centers around the fast-moving consumer goods industry. While this emerging sector is fueled by innovative food technology, the entry barriers are relatively low. Future research could validate our findings of VC interests on entry pattern by exploring similar dynamics in diverse industries with distinct characteristics. Another interesting avenue for future work is to investigate the extent to which the influence of VCs on product market positioning extends beyond VC-backed companies. Existing research indicates that startups with multiple labels are more appealing to VC investors (Pontikes, 2012). Future studies could provide a more comprehensive understanding of when VCs select startups with multiple logics and when they actively promote the adoption of those logics.

Chapter 4 Funding Sustainability-driven Ventures: The Role of Limited Partners

4.1 Introduction

In recent years, institutional investors have shown a growing appetite for investments that generate positive and long-term social impact beyond mere financial gains, with the demand for Environmental, Social, and Governance (ESG) products outstripping the available supply. For instance, according to a 2022 survey conducted by PwC among 250 institutional investors, nearly 90% of respondents urge asset managers to be more proactive in creating new ESG investment options (PwC 2022). Furthermore, there is a mounting consensus to integrate ESG considerations into investment processes across various asset classes, through active and responsible ownership (see, for instance, the United Nation's six Principles for Responsible Investment).[21]

The increasing importance of sustainable and responsible investing has also received substantial attention in academic research (for a review, see Section 3 of Liang and Renneboog (2021)). Recent studies have documented institutional investors' increasing preference for sustainability and ESG-related performances within various asset classes, including fixed income (Flammer 2021), mutual funds (Bialkowski and Starks 2016, Hartzmark and Sussman 2019, Riedl and Smeets 2017), hedge funds (Liang et al. 2022), and institutional ownership of publicly traded firms (Dyck et al. 2019, Ilhan et al. 2023, Krueger et al. 2020, Liang and Renneboog 2020). While these studies focus on public markets and relatively liquid products, little is known about whether and to what extent institutional investors' preference for

[21] See United Nations' principles for responsible investment: https://www.unpri.org/about-us/what-are-the-principles-for-responsible-investment

sustainability manifests in private markets. Traditionally considered as an "alternative asset class", private equity[22] has experienced dramatic growth and become an indispensable component of institutional investment portfolios (Batt and Appelbaum 2021, Sensoy et al. 2014).[23]

Regarding sustainable and responsible investing within private equity, existing academic studies have predominantly focused on institutional investors' commitments to impact funds (e.g., Barber et al. 2021, Chowdhry et al. 2019, Cole et al. 2023, Geczy et al. 2021), i.e., funds that explicitly state the dual objectives of generating positive social impact in addition to financial returns. However, given that impact funds represent merely 1-3% of all funds investing in private equity[24], institutional investors' engagement with sustainability and ESG-related issues when investing through conventional funds (that prioritize financial returns) remains poorly understood.

In this paper, we investigate whether institutional investors' preference for sustainability extends beyond impact funds and manifests across the entire asset class of private equity. Specifically, we examine institutional investors who invest in entrepreneurial startups through venture capital (VC) funds, assuming their role of limited partners (LPs).[25] While LPs typically refrain from direct involvement in a fund's daily operations to maintain limited liability (Batt and Appelbaum 2021), they may still wield substantial influence over a fund's overarching investment strategies. Extant research comparing independent and different types of captive VC firms[26], as well as investigation into performance and investment strategies

[22] In this paper, when referring to private equity, we are encompassing the broader scope of investments made in privately-held companies. This includes various strategies such as venture capital and growth equity.
[23] For example, in the 2023 Global Private Markets Survey by BlackRock, 43% of respondents report plans to "substantially increase" their private equity holdings. See https://www.blackrock.com/institutions/en-us/literature/whitepaper/global-private-markets-survey.pdf
[24] This is an estimation based on the samples in Barber et al. (2021) and Cole et al. (2023).
[25] As we show in the data section, approximately 90% of equity investments in private companies originate from VC funds, which primarily target startups at various stages of development. Consistent with Barber et al. (2021), we adopt the term "VC funds" to loosely encompass these entities throughout this paper.
[26] The main types of captive VC firms include corporate VC, bank-owned, and government-sponsored VC firms.

across different types of institutional investors (Lerner et al. 2007, Sensoy et al. 2014), suggests that sources of funding shape VC investment styles and activities, such as geographical focus (e.g., Hochberg and Rauh 2013, Mayer et al. 2005), industry choice (e.g., Hellmann et al. 2008), stages of financing (e.g., Mayer et al. 2005, Winton 2003), and syndication size (e.g., Dushnitsky and Shapira 2010). In this research, we examine how the sustainability orientation of VC funds is shaped by LPs' preferences for social impact. In particular, we focus on a fund's portfolio composition of sustainability-driven (SD) ventures, characterized by their dual objectives of generating economic profit while also making a positive social and environmental impact (Shepherd and Patzelt 2011). Our research question is motivated by recent surveys on VC general partners (GPs) that report "a higher propensity to engage in ESG investing as a result of *growing demand from their LPs*" (Botsari and Lang 2020). Not only has the sustainability angle been largely overlooked by existing research addressing the influence of LPs in shaping the investment strategies of VC funds, but it also holds practical implications for SD ventures seeking to expand their funding opportunities.

We build on research by Barber et al. (2021), which has shown that certain types of LPs—development organizations, foundations, public pension funds, and financial institutions—willingly trade financial returns for social impact when investing through impact funds, which are expected to have lower performance than conventional VC funds. Hence, we compare the sustainability orientation of a VC fund backed by LPs with high versus low willingness-to-pay (WTP) for social impact. We expect that LPs with high WTP for social impact might pressure their GPs to include more SD ventures in their investment portfolio. We further predict that this positive association between a fund having high WTP LPs and investing in more SD ventures will be more pronounced: (a) when there is a misalignment in investment objectives between the fund and its LPs; and (b) when the fund is more malleable to demands from LPs.

We empirically test these predictions by drawing a large sample of 4,419 global VC funds established between 1995 and 2016, sourced from the Pitchbook dataset. These funds are managed by GPs whose primary investment strategy focuses on VC or growth equity. We track each fund's investment histories, as well as its GPs and LPs. We rely on Barber et al. (2021) to classify LPs into high versus low WTP for social impact based on their institutional investor type. Development organizations, foundations, public pension funds, and financial institutions are classified as high WTP LPs, whereas private pension funds, endowments, corporations, wealth managers, and institutional investors with diverse mandates are classified as low WTP LPs.[27] To categorize SD ventures, we build upon the methodologies of Barber et al. (2021) and Zhang (2023) and use a text-based approach to study their business description in Pitchbook.

Our results show that funds predominantly backed by high WTP LPs have, on average, significantly more SD ventures in their portfolio compared to funds supported by low WTP LPs. Further, this effect is solely evident in cases where there is a misalignment of objectives between high WTP LPs and the fund, specifically, in conventional funds (as opposed to impact funds), and in funds located in countries with weak (instead of strong) norms toward sustainability performance. Additionally, the effect of high WTP LPs is more pronounced in funds managed by first-time and young GPs, which, we conjecture, are more likely to adapt to the pressure exerted by LPs. Our main results remain robust when employing alternative classifications of WTP for social impact, as well as when we restrict our analysis to a subsample of fully invested and liquidated funds. We also rule out the alternative explanation that the observed differences in the portfolio composition of SD ventures are due to funds' differences in risk appetite.

[27] As we show in the Data section below, we validate this classification by examining commitments in impact funds by different types of LPs.

Next, we conduct tests to address potential selection effects. We consider the possibility that high WTP LPs select funds that are expected to include a higher share of SD ventures in their portfolio. To mitigate this, we introduce an instrumental variable specification. We follow prior literature (e.g., Alvarez-Garrido and Dushnitsky 2016, Bottazzi et al. 2008) that leverages the local availability of selected characteristics as an instrumental variable. In our specific context, we focus on the availability of low WTP LPs investing in a given vintage year where a fund is located. The time- and location-specific availability of LPs introduces exogenous variation into a fund's capital commitments from high versus low WTP LPs, but does not directly influence the outcome of the portfolio composition of SD ventures. Our results remain robust when using this specification.

Lastly, we explore the mechanisms through which LPs can influence the sustainability orientation of funds. Prior literature suggests that LPs can apply pressure on GPs either directly through governance measures (Botsari and Lang 2020, Da Rin and Phalippou 2017) or indirectly by signaling a threat not to reinvest in subsequent funds managed by the same GPs (Lerner et al. 2007). However, we find little evidence that funds underperforming in selecting sustainable startups are less likely to receive reinvestment from high WTP LPs. Consequently, we conjecture that LPs primarily wield influence over fund sustainability orientation through private negotiations and continuous monitoring of ongoing fund portfolios. This finding aligns with Batt and Appelbaum's (2021) argument that LPs' reinvestment decisions may at times possess limited disciplinary power.

We make two primary contributions to extant literature. First, our findings underscore the crucial role of LPs in shaping the investment objectives and styles of VC funds, challenging the conventional view of LPs as passive capital suppliers (Batt and Appelbaum 2021, Botsari and Lang 2020, Da Rin and Phalippou 2017). Specifically, we show how LPs' varying preference for social impact shapes a fund's investment in SD ventures. Further, we investigate the conditions under which LPs' influences are more or less pronounced. In turn, our findings enrich the broader literature of investor engagement on ESG issues through active ownership (Barko et al. 2021, Gollier and Pouget 2022, Hoepner et al. 2024).

Second, we advance understanding of socially responsible investments and impact investing (e.g., Barber et al. 2021, Cole et al. 2023, Kovner and Lerner, 2015, Renneboog et al. 2008) by uncovering that LPs' preferences for social impact not only influence their selection of impact funds but also shape the portfolio composition of SD ventures when they invest through conventional VC funds without an explicitly stated dual mission. Given the limited supply of impact funds, which represent only approximately 1-3% of all private equity funds (Barber et al. 2021; Cole et al. 2023), addressing the heterogeneity in the sustainability orientation of conventional funds is particularly relevant. Further, we link this heterogeneity to the origins of capital, specifically LPs exhibiting differing levels of WTP for social impact (Barber et al. 2021). In doing so, we extend the research on how investors' preferences for sustainability manifest in their investment decisions (Dyck et al. 2019, Flammer 2021, Hartzmark and Sussman 2019, Ilhan et al. 2023, Krueger et al. 2020, Liang and Renneboog 2020, Liang et al. 2022), broadening the exploration to the asset class of private equity.

4.2 Theoretical Background and Hypotheses

The standard structure of VC markets involves VC firms creating funds to pool capital from institutional investors and high-net-worth individuals. These funds, as investment vehicles, are then deployed for equity investments in entrepreneurial startups (Da Rin et al. 2013). The fund contract typically takes the form of a partnership, where VC firms, also known as the fund's general partners (GPs), bear the responsibility for the day-to-day operations of the fund, assuming unlimited liability, and usually commit about 2% of their own equity to the fund. In contrast, investors, termed limited partners (LPs), commit the remaining 98% of the capital typically for a ten-year period, and maintain limited liability by abstaining from direct involvement in the fund's operations. Throughout the fund's lifecycle, GPs are responsible for selecting and monitoring the portfolio of startups.

The exploration of institutional investors' preferences for sustainability has been studied in various asset classes (Bialkowski and Starks 2016, Dyck et al. 2019, Flammer 2021, Hartzmark and Sussman 2019, Ilhan et al. 2023, Krueger et al. 2020, Liang and Renneboog 2020, Liang et al. 2022, Riedl and Smeets 2017). For instance, Flammer (2021) shows that, by issuing green bonds, companies credibly signal their commitment toward the environment, which translates into higher environmental performance post-issuance, attracting a greater share of long-term and green investors. Similarly, examining capital flows in U.S. mutual funds immediately after the publication of these funds' sustainability ratings, Hartzmark and Sussman (2019) observed a reallocation of capital away from funds with lower sustainability ratings to those rated as highly sustainable. Likewise, hedge funds endorsing United Nations Principles for Responsible Investment (UNPRI) attract greater investor flows despite underperformance (Liang et al. 2022).

Institutional investors not only screen and select ESG products, but they may also actively engage with portfolio companies to enhance their ESG performances. Dyck et al. (2019) found that institutional ownership is associated with increased environmental and social performance among publicly traded firms, especially when investors are signatories to the UNPRI and when they come from countries exhibiting a greater demand for sustainability performance. Importantly, they also show that investors may actively push for improving ESG performance through both public shareholder proposals and private negotiations. In a similar vein, Krueger et al.'s (2020) survey study on global institutional investors indicates that particularly long-term, larger, and ESG-oriented investors can proactively engage with their portfolio companies regarding climate risks. They do so through multiple channels, including discussions with top management teams, submitting shareholder proposals, and voting against projects with climate risk concerns. Furthermore, the majority of investors consider risk management and engagement to be the preferred approach for addressing climate risks, rather than divestment.

Overall, these findings not only underscore the appetite among institutional investors for sustainability and their active advocacy, but also suggest that this preference may hold relevance across various asset classes. Given that private equity has become a fundamental component of institutional investment portfolios (Sensoy et al. 2014), it is particularly interesting to study institutional investors' preferences for sustainability when they invest in entrepreneurial startups through VC funds.

Prior research has rarely examined the relation between sources of capital for VC funds (i.e., types of LPs) and GPs' investment activities. A notable exception is Mayer et al. (2005), which differentiated VC funds backed by individuals, banks, corporations, insurance companies, pension funds, and governments. Their findings indicate that the source of funds influences investment activities in terms of both investment stages and geographical focus. Specifically, funds backed by financial institutions tend to invest more in later-stage startups, while those backed by individuals and corporations prefer early-stage startups. Additionally, bank- and government-backed funds often invest in local startups, whereas funds supported by insurance companies, corporations, and individuals have more global coverage. Differences in investment activities among funds from various sources of capital indicate that different types of LPs have distinct investment objectives and requirements. Research comparing independent and captive VC firms indirectly supports the argument that distinct sources of capital have unique investment objectives, consequently shaping funds' investment styles. For example, corporate VC firms primarily select startups that offer strategic benefits to the technology portfolio of their main LP, the corporate VC's parent company (Dushnitsky 2012). Similarly, bank-affiliated VC firms may deviate from the sole focus on maximizing investment returns in order to secure potential future banking income from the companies in their fund's portfolio (Lerner et al. 2007).

While LPs cannot play an active role in management decision-making (Batt and Appelbaum 2021), they also face limited exit options throughout the typical ten-year lifespan of a fund, unlike investors in public corporations. Given these constraints, the question arises: How can LPs still exert influence over the sustainability orientation of VC funds, despite not being directly involved in the specific investment decisions made by GPs?

We posit two potential channels for this influence. First, LPs can impact the decision-making process within VC firms. Recent findings from a pan-European survey on VC firms' ESG considerations highlight the growing demand from LPs as one of the most important factors in shaping GPs' ESG policies and procedures (Botsari and Lang 2020). Notably, VC firms face demand from LPs in three key aspects: filtering out startups that do not meet specific ESG criteria; incorporating an ESG expert into the investment team; and actively monitoring ESG performances of their portfolio companies. Similarly, research conducted by the United Nations concerning public pension and sovereign wealth funds has identified that leading ESG-oriented LPs share ESG resources, oversee the adoption of ESG procedures and processes among GPs, request detailed reports on stewardship activities, and diligently monitor and evaluate GPs' ESG strategies (United Nations 2020). This mechanism is supported by anecdotal evidence as well. For instance, the 2023 Universities Superannuation (USS) Stewardship Code Report[28] states, "*We monitor the GPs to ensure that ESG issues are being properly managed and to encourage improvements in ESG performance. ... The RI (responsible investment) team undertakes research into the portfolio companies or other assets*

[28] USS is UK's public pension fund, serving as principle pension scheme for universities and higher education institutions. See https://www.uss.co.uk/how-we-invest/responsible-investment

in which a GP has invested, including any co-investments, to identify ESG risks or opportunities that can be interrogated further with the GP."

Second, LPs can indirectly exert pressure on GPs through the flow of capital into GPs' subsequent funds. Unlike assets in public markets, which are relatively liquid, investments in VC funds involve long-term commitments that cannot be easily withdrawn. Therefore, the decision to reinvest in a GP's next fund serves as the primary means through which LPs can apply governance pressure on GPs (Lerner et al. 2007). If GPs' investment decisions fail to meet LPs' expectations regarding ESG performance, it is probable that GPs may suffer from reputational damage and encounter challenges in raising capital for their follow-on funds. This indirect mechanism might be less effective when assessing financial performance because typically GPs start fundraising for a follow-on fund after the early-year investment period has ended, and actual performance remains quite uncertain until almost the end of the ten-year duration of the fund (Batt and Appelbaum 2021). However, the focus on investments into sustainable investees makes it immediately clear and measurable whether LPs' expectations regarding the sustainable performance are met or not.

Following these arguments, we further draw on studies that highlight varying levels of WTP for social impact among institutional investors. Specifically, Barber et al. (2021) found that certain types of LPs, including development organizations, foundations, public pension funds, and financial institutions, willingly trade financial returns for social impact when investing in impact funds that are expected to have lower performance than conventional funds. In contrast, endowments, private pension funds, corporations, and institutional investors with diverse mandates have negligible WTP for social impact. Consequently, we expect that LPs with high WTP for social impact are more inclined to exert influence on VC funds, encouraging a greater focus on sustainability in their investment decisions.

Overall, we hypothesize that:

Hypothesis 1. VC funds backed by LPs with high WTP for social impact have a higher sustainability orientation than VC funds backed by LPs with low WTP for social impact.

Next, we explore under what conditions high WTP LPs are more inclined to shape the sustainability orientation of VC funds. We build on existing research on institutional investors (see, for instance, Aghion et al. 2013) by assuming that exerting influence is costly for LPs. These costs might include lengthy negotiations regarding ESG criteria at the time of capital commitment, ongoing monitoring of GPs' investment targets, potential tensions with GPs who bear unlimited liability for their investment choices, and the possibility of forgoing opportunities when exiting follow-on investments. Consequently, LPs will only seek to influence GPs when deemed necessary.

When the sustainability preferences of LPs and GPs are congruent, GPs are likely to make decisions aligning closely with those that LPs would make if they had decision-making power. In such instances, there is minimal need for LPs to exert influence. Conversely, significant disparities in preferences regarding the sustainability focus of the fund's portfolio are anticipated to magnify the impact of LPs with high WTP for social impact. Specifically, we consider two contingencies that might explain the misalignment of preferences for sustainable investees: a) funds without an explicit impact mission, b) funds operating in regions with weak norms for sustainability.

First, impact funds explicitly declare a dual mission for both financial returns and social impact. When high WTP LPs allocate capital to impact funds, the investment objectives between the fund and its LPs are largely aligned. Thus, the need for high WTP LPs to demand investments in sustainability becomes less relevant in impact funds. This is consistent with the findings of Brest and Born (2013), emphasizing a balanced approach of impact funds. However, since impact funds constitute only around 1-3% of all private equity investments (Barber et al.

2021; Cole et al. 2023), a potential misalignment of investment objectives arises when high WTP LPs invest through conventional funds that seek to maximize financial returns. Such conventional funds are structured with a clear focus on financial profitability (Lerner and Gompers 2001).

Second, social norms toward sustainability and ESG performance vary significantly across different countries. Dyck et al. (2019) discovered that only European institutional investors significantly influence a public firm's environmental and social performance, in contrast to investors from other regions. This finding aligns with Barber et al. (2021), who observed that European LPs consistently exhibit a higher WTP for social impact compared to LPs from other regions. For fund managers, operating within regions where sustainability norms are strong means encountering a more consistent demand for sustainable practices from a broader set of stakeholders. This is particularly evident as they engage in local networking and capital-raising activities. Conversely, in countries with weaker sustainability norms, fund managers face a wider preference gap with high WTP LPs. Consequently, we expect a heightened demand for sustainability from high WTP LPs when funds are situated in countries with weaker norms regarding ESG performance.

Summarizing, we hypothesize that:

Hypothesis 2. The positive association between funds having high WTP LPs and a higher sustainability orientation is more pronounced when there is a misalignment of investment objectives between the fund and its LPs. Specifically, in a) funds without an impact mission, b) funds in countries with weak norms for sustainability.

While there might be heterogeneity in the incentives of high WTP LPs to influence the sustainability orientation of VC funds (as proposed in Hypothesis 2), ultimately the outcome will also depend on how funds respond to these influence attempts. Not all funds readily adjust to demands from LPs: some may be more responsive, others less so. Specifically, we expect that certain funds, particularly those under the management of first-time and young GPs, are more inclined to accommodate LPs' preferences and demands. On the one hand, these funds lack a well-established track record and reputation for successfully selecting and managing portfolio companies. As a result, they face the imperative of leveraging their networks and aligning with LPs' preferences to build their reputation (Hochberg et al. 2007). On the other hand, adapting to preferences and demands from LPs aligns with the needs of less-experienced GPs to establish a long-term rapport with their LPs (Metrick and Yasuda 2011), facilitating the fundraising process of their subsequent funds. This is consistent with findings indicating that younger firms are more prone to modify their strategies to align with market conditions and investor expectations (Gompers et al. 2010). Therefore, we expect that funds managed by first-time and young GPs are likely to exhibit greater malleability, as they seek to establish themselves in the highly competitive market environment. On the contrary, funds with an established reputation and a track record of successful fundraising can exploit the significant power asymmetries in the GP-LP relationship (Batt and Appelbaum 2021) and shield themselves from the influence of the LPs. Therefore, we posit our third hypothesis as:

Hypothesis 3. The positive association between funds having high WTP LPs and a higher sustainability orientation is more pronounced when the fund is more malleable to LPs' influence, that is, funds managed by first-time and young GPs.

4.3 Methods

4.3.1 Data and Sample

We obtain data on funds, their GPs, LPs, and funds' portfolio composition from Pitchbook[29], a fast-evolving dataset that is reported to have better coverage, provide more

[29] Pitchbook version of updates: Dec. 2022.

accurate funding information (Retterath and Braun 2020), and be more transparent in terms of identifying fund names and general partners (Kaplan and Lerner 2017). The Pitchbook dataset is widely used by practitioners, serving as a data provider for the National Venture Capital Association, and is increasingly employed in academic research (e.g., Cole et al. 2023, Gompers et al. 2021).

We start our sampling procedure (summarized in Appendix A Table 4.7) by identifying 25,325 unique funds that made equity investments from Pitchbook's dataset. Since we are interested in funds managed by general interest VCs, our initial approach involves filtering out 2,533 funds managed by GPs whose primary focus does not revolve around VC or growth equity.[30] Next, we excluded 55 funds overseen by investors with specific mandates, such as those centered on real estate or infrastructure, as well as 170 SBIC[31] funds. We then checked the funds' investment history and excluded 12 funds that had solely non-VC-related transactions, such as grants. Furthermore, we confine our selection of funds to those established within the 22-year span from 1995 to 2016. Our observation starts in the mid-1990s, coinciding with the rising prominence of sustainability, notably catalyzed by pivotal events such as the Kyoto Protocol. The upper limit of 2016 allows for an apt time window to track a fund's activities post-establishment, considering that VC funds typically take up to three years to construct their initial portfolios. Subsequent capital is commonly earmarked for follow-on deals, aimed at nurturing and scaling ventures within the existing portfolio. We further excluded 5 canceled funds and 9 ongoing open funds, which retain the potential to secure

[30] These funds are managed by GPs whose primary investor type is categorized as one of the following: Angel (individual), Corporate Development, Corporate Venture Capital, Corporation, Family Office, Fund of Funds, Fundless Sponsor, Government, Hedge Fund, Holding Company, Investment Bank, Leasing, Lender/Debt Provider, Limited Partner, Merchant Banking Firm, Mutual Fund, Other, PE-Backed Company, Secondary Buyer, Sovereign Wealth Fund, Special Purpose Acquisition Company, University, VC-Backed Company.

[31] Small Business Investment Company (SBIC) is licensed by the Small Business Administration (SBA), a U.S. government agency. The objective of SBIC program is to provide venture capital and debt financing to U.S. small companies.

capital commitments from new LPs. At the level of portfolio companies, we follow Cole et al. (2023) and do not include companies that never received VC investments.[32] Additionally, to avoid having funds that only make one-off investments, we dropped 3,051 funds that have less than three companies in their portfolio. Lastly, we require that a fund has at least information about one LP in our dataset and dropped 3,769 funds that have no LP information.

The sampling process left us with an analysis sample of 4,419 funds[33], managed by 2,197 unique GPs, investing in 45,872 ventures, and receiving capital commitments from 6,142 unique LPs.

4.3.2 Measures

Dependent variable: Fund sustainability orientation. We define a fund's *sustainability orientation* as the proportion of its portfolio companies that are categorized as sustainability-driven. To identify SD ventures, we employ a dictionary-based approach (Barber et al. 2021, Zhang 2023), which involves conducting a keyword search within a venture's business description. In particular, we expanded the keyword lists provided by Barber et al. (2021) and Zhang (2023), and divided the keywords into two categories that address environmental and social issues, respectively (see Appendix B). We then cross-referenced these lists with each company's business description provided by Pitchbook, which outlines a venture's primary activities. This information has been used in previous research to identify ESG-related companies (Zhang 2023). Below, we provide an example of a company's business description from our sample, omitting the company name.

> *"[...] is a Sweden-based company active in the field of* ***clean energy****. It develops, manufactures, and produces* ***environment****-friendly electrical power*

[32] These companies have either solely received grants or engaged exclusively in buyout deals as their initial or sole transactions.
[33] The size of our sample is comparable to that of Barber et al. (2021), who identified 4,659 funds with LP information from Preqin's Investor Intelligence database. Our sample is slightly smaller, possibly because we further require a minimum of three portfolio companies for each fund.

systems for stationary, marine, off-road, and on-road segments. [...] Its technology combines high efficiency with a compact format and contributes to increased ***energy efficiency*** *as well as a significant reduction in emissions of* ***carbon*** *dioxide and harmful particles regardless of application."*

A positive match is identified if any of the sustainability-related keywords listed in Appendix B is detected in a startup's business description. In the example above, the bolded phrases indicate matches with keywords related to environmental issues. Consequently, we classify this startup as sustainability-driven. To ensure accuracy, we manually verified matched phrases and eliminated any false positives. This process yielded two dummy variables for each venture, representing its environmental and social orientation. Subsequently, a venture is classified as sustainability-driven if it exhibits either or both of these orientations. We further provide an overall summary of the portfolio ventures and the availability of SD ventures throughout the years covered by our sample in Appendix B.

Independent variable: Fund backed by High WTP LPs. We created a dummy variable indicating whether a fund is predominantly backed by high WTP LPs. Barber et al. (2021) discovered that specific types of LPs are inclined to trade financial returns for social impact when investing in impact funds, even if these funds are anticipated to yield lower performance compared to conventional funds. [34] Among the nine LP types studied, development organizations, financial institutions, public pensions, and foundations consistently demonstrate a higher WTP for social impact than wealth managers, institutional investors (with diverse

[34] Barber et al. (2021) uses a discrete choice hedonic model to estimate investors' WTP for impact. Specifically, investor's utility of investing in a fund in a given vintage year is estimated based on various fund characteristics, including an impact fund dummy and ex-ante expected financial returns. The WTP for social impact is then calculated as the ratio between the coefficient on impact fund dummy and the coefficient on expected return. In Barber et al. (2021)'s sample of funds established between 1995 and 2014, the average WTP for impact is estimated at 13-18 percentile. However, when estimating the WTP by LP type, development organizations, financial institutions, and public pensions have a large and positive WTP for impact (13 to 27 percentile ranks which translates to 2.5-6.2 ppts lower IRR ex ante for impact funds); foundations also have a positive but small WTP for impact (6 percentile ranks); in contrast, endowments, corporations, institutional managers, wealth managers, and private pensions have negligible WTP for impact.

mandates), corporations, private pensions, and endowments. In alignment with their methodology, we gather information on each LP's type from Pitchbook and classify them into the nine LP types as defined by Barber et al. (2021). For each LP, we then create a dummy variable indicating high versus low WTP for social impact. Appendix A Table 4.8 provides a detailed account of the grouping of LP types.

To validate the categorization of LPs into high and low WTP based on their type, we analyzed the average number of impact funds invested by different types of LPs. Specifically, we rely on the list of impact investors compiled by Cole et al. (2023) and tracked LPs' commitments to funds managed by these impact investors. Consistent with the findings from Barber et al. (2021), we observed that development organizations committed capital to the highest number of impact funds, followed by foundations, financial institutions, and public pension funds (details reported in Appendix A Table 4.9). Therefore, we are confident in the validity of the categorization of LP's high versus low WTP for social impact.

At the fund level, a fund is defined as predominantly backed by high WTP LPs (assigned a value of 1 and 0 otherwise) if it has 50% or more of its LPs classified as high WTP for social impact. It is worth noting that all the sample funds in our study have already closed, with minimal likelihood of securing additional LP commitments. In the robustness check section below, instead of using a binary dummy variable to indicate whether a fund is predominantly backed by high WTP LPs using a 50% cut-off, we also present findings based on the continuous fraction of high WTP LPs in a fund. Additionally, we analyze a subsample of funds that are either fully invested or liquidated.

4.4 Results

4.4.1 Descriptive Statistics

Fund characteristics. We gathered information on fund size, vintage, type, and location. Additionally, we calculated the size of a fund's portfolio, the count of committed LPs, and the proportion of portfolio ventures undergoing liquidity events like mergers and acquisitions, IPOs, or going out of business. Furthermore, we created two dummy variables: *First Fund,* indicating whether a fund is the first one by a GP; and *Co-managed Fund*, indicating whether a fund is jointly managed by multiple GPs. To evaluate a fund's investment objective in sustainability and social impact, we introduced a dummy variable, *Impact Fund.* This variable is determined based on the list of 275 impact investors[35] compiled by Cole et al. (2023). They define impact firms as those with the explicit dual objective of generating both social and financial returns. Their sample of impact investors is compiled based on various established resources on impact investing with manual qualitative checks, and is reported to be the most comprehensive dataset on impact investors. In our data, if a fund is managed by an impact investor, it is classified as an impact fund due to their specific mandates that prioritize investments in SD ventures. In the robustness check section below, we also introduce an alternative measure for a fund's preference for ESG-related investing, based on GP's investment preferences for either "Seeks ESG investments," "Seeks Impact investments," or "Invests in MWBE (Minority and Women-owned)," as reported in Pitchbook.

In Table 4.1 Panel A, we present descriptive statistics for the 4,419 funds established between 1995 and 2016 in our sample. On average, these funds have a vintage year of 2008 and a size of 357.58 million USD[36], although there is substantial variation across funds. Approximately 29% of the sample funds are characterized as the first fund of their GPs.

[35] These are VC or private equity firms that focus exclusively on impact investing.
[36] The average fund size is comparable to that ($313 million) of Lerner et al. (2007) and larger than that ($204.6 million) in Barber et al. (2021). The smallest fund in our sample is $0.02 million, located in Columbia. The largest fund in size is $21.7 billion, which is a buyout fund. As also reported in Lerner et al. (2007), buyout funds are in general much larger in size. Among the group of funds exceeding $5 billion in size within our sample, 90% are buyout funds.

Although infrequent, 5% of the funds in our sample have more than one GP. The average fund has eight LPs[37] and invested in 21 ventures.[38]

156 (4%) funds from our sample are classified as impact funds.[39] About 43% of the sample funds have made investments in SD ventures, although the average share of such companies in the portfolio is 6%. It is worth noting that the average proportion of socially-driven ventures (1%) in a fund's portfolio is much lower than that of environmentally-driven ventures (5%). On average, 43% of the ventures within a fund's portfolio were acquired, and 8% went public, in contrast to an average of 13% of ventures that went out of business.

The majority of funds in our sample (59%) are identified as general interest venture funds, while 19% focus on early-stage ventures, 11% on later-stage ventures, and 11% are buyout funds. In terms of geographical distribution, 59% of the funds are located in the United States, 19% in developed Europe, and 23% in the rest of the world.

Two GP-fund dyad-level variables are particularly relevant for our study. First, to evaluate GPs' expertise as fund managers and potentially reflect their fundraising capability, we constructed a proxy variable *GP Fundraising Experience*, defined as the number of years between a fund's vintage year and the first year in which its respective GP establishes a VC fund.[40] The average GP has 6.44 years of fundraising experience at the time of a fund's vintage year. Second, we acknowledge that the effect of high WTP LP on fund sustainability orientation might be due to selection. To help control for the selection effect, we created a dummy variable indicating whether a fund is managed by GPs who had prior experience in

[37] The three funds with the largest number of LPs are all over 1 billion USD in size, and received capital commitments from 238, 174, and 166 LPs respectively.
[38] As we illustrated in constructing the sample, we required that a fund has at least three ventures in their portfolio. Remarkably, the top three funds with the largest number of portfolio companies in our sample each have over 400 ventures. Notably, all three are early-stage venture capital funds, with two managed by Y Combinator and one by 500 Global.
[39] While the sample size of impact funds in our study is rather small, it is comparable to Barber et al. (2021), who identified 159 impact funds with a vintage year ranging from 1995 to 2014.
[40] For the 5% of funds in our sample that have more than one GP, we used information of the GP with more years of VC experience.

investing in SD ventures by the time of a fund's vintage year. About 37% of funds in our sample have GPs with such investments at the time of fund establishment.[41]

Next, we turn to our key predictor variable. The average fund of our sample has 45% of its LPs identified as having high WTP for social impact. Based on our definition, 49% of the sample funds are classified as funds predominantly backed by high WTP LPs (with 50% or more of its LPs as high WTP). In the following Table 4.2, we show several stylized facts pertaining to our main outcome of interest: fund-level sustainability orientation. On average, across all vintage years, funds predominantly backed by high (low) WTP LPs have 7% (5%) of its portfolio companies identified as sustainability-driven. In Figure 4.1 below, we illustrate the average share of SD ventures in a fund's portfolio, comparing funds backed by high WTP LPs to those backed by low WTP LPs, across different fund vintage years. There is a noticeable upward trend for both types of funds to invest in SD ventures, particularly in the 2000s. More importantly, funds backed by high WTP LPs consistently exhibit a greater share of SD ventures compared to their low WTP counterparts across the majority of years, providing some initial support for our predictions. It is worth noting that the difference in the share of SD ventures was more prominent before the 2008 financial crisis compared to the period after the crisis. This pattern is consistent with previous literature suggesting that in the post-crisis era, firms' environmental and social performances are becoming increasingly appealing, even for investors primarily motivated by financial considerations (Dyck et al. 2019).

[41] We further report efforts to control for potential selection effect in the section of instrumental variable specification below.

Table 4.1 Descriptive Statistics

Panel A: Fund Characteristics					
Variables	N	Mean	Std. Dev.	Min	Max
Fund Vintage	4419	2008.24	6.24	1995	2016
Fund Size (mil. USD)	4277	357.58	1074.86	.02	21700
First Fund	4419	.29	.45	0	1
Comanaged-Fund	4419	.05	.22	0	1
Number of LPs investing in Fund	4419	8.02	13.52	1	238
Fund Portfolio Size	4419	21.09	28.96	3	481
Impact Fund	4419	.04	.18	0	1
Fraction High WTP LPs	4419	.45	.36	0	1
Fund backed by High WTP LPs	4419	.49	.5	0	1
Fund Has SD ventures	4419	.43	.49	0	1
Sustainability Orientation (Fraction of SD ventures)	4419	.06	.12	0	1
Fraction of Socially-driven ventures	4419	.01	.03	0	.67
Fraction of Environmentally-driven ventures	4419	.05	.11	0	1
Fraction of MA ventures	4419	.43	.28	0	1
Fraction of IPO ventures	4419	.08	.12	0	1
Fraction of Out-of-Business ventures	4419	.13	.14	0	1
Fund Type					
General Interest Venture Fund	4419	.59	.49	0	1
Venture Capital – Early Stage	4419	.19	.39	0	1
Venture Capital – Later Stage	4419	.11	.31	0	1
Buyout	4419	.11	.32	0	1
Fund Global Regions					
United States	4419	.59	.49	0	1
Developed Europe	4419	.19	.39	0	1
Rest of World	4419	.23	.42	0	1
Fund-GP characteristics					
GP Fundraising Experience	4419	6.44	7.62	0	47
GP Had Experience in SD ventures	4419	.37	.48	0	1

Panel B: LP Characteristics by LP Type						
WTP	LP Type	N	%	Total Commitments	Percent Commit in VC & PE[42]	Number of Sample Funds
High	Foundation	676	11.01	26.69	.65	6.10
	Financial Institution	639	10.40	28.23	.77	6.10
	Public Pension Fund	317	5.16	152.15	.55	21.11
	Development Org	207	3.37	23.14	.92	5.43
Low	Wealth Manager	1,486	24.19	5.01	.96	2.01
	Corporation	996	16.22	3.47	.96	1.53
	Private Pension Fund	849	13.82	45.95	.63	8.77
	Institutional	783	12.75	27.53	.94	8.07
	Endowment	189	3.08	28.77	.81	6.90
	Overall	6,142	100.00	27.06	.83	5.78

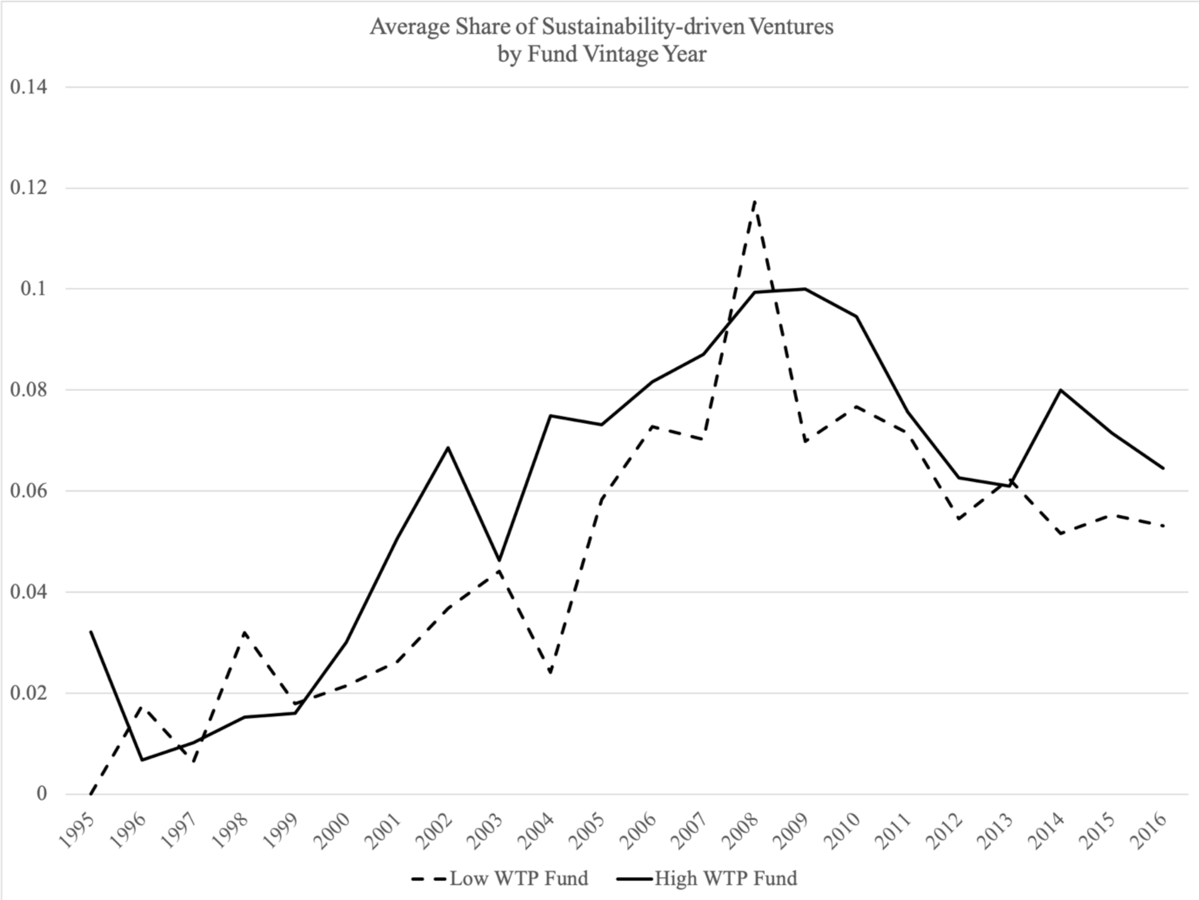

Figure 4.1 Average Share of Sustainability-driven Ventures by Fund Vintage Year

Table 4.2 further shows that impact funds have 24% of its portfolio companies composed of SD ventures, compared to 5% of conventional funds. In terms of fund type, funds targeting later-stage ventures have a higher share (7%) of SD ventures than those targeting early-stage ventures (5%), general interest venture funds (6%) and buyout funds (6%). The share of SD ventures also differs by location. Funds located in developed Europe have the highest share (8%) compared to those based in the United States (5%) and in other places of the world (6%). In addition, being a first fund of a GP is associated with a higher share (7%) of SD ventures than non-first funds (5%). Moreover, funds managed by GPs with prior

[42] This percentage is calculated within the asset class of alternative investments based on data reported in Pitchbook, i.e. capital commitments into VC, PE, real estate, debt etc., not including LPs' commitments into other asset classes, such as stocks.

experience in investing in SD ventures have a higher share (8%) than those without such experiences (4%).

Table 4.2 Sustainability Orientation by Fund Characteristics

	No. of Funds	Mean Share SD Ventures
Fund WTP		
Fund backed by High WTP LPs	2,144	.07
Fund backed by Low WTP LPs	2,275	.05
Impact versus Conventional		
Impact Fund	156	.24
Conventional Fund	4,263	.05
Fund Type		
Venture Capital - General	2,596	.06
Venture Capital – Early Stage	854	.05
Venture Capital – Later Stage	469	.07
Buyout	500	.06
Fund Location		
Developed Europe	826	.08
United States	2,590	.05
Rest of the World	1,003	.06
First Fund by GP		
First Fund	1,291	.07
Not First Fund	3,128	.05
GP experience in SD Ventures		
GP with experience in SD	1,644	.08
GP without experience in SD	2,775	.04

LP characteristics. Table 4.1 Panel B presents the descriptive statistics of our sample LPs by type. In terms of LP count, foundations (11.01%) and financial institutions (10.40%) are the largest group for high WTP LPs, followed by public pension funds (5.16%) and development organizations (3.37%). For LPs categorized as low WTP, wealth managers are the largest group (24.19%), followed by corporations (16.22%), private pension funds (13.82%), and diversified institutional investors (12.75%). Endowments are the smallest group (3.08%) in our sample.

This pattern does not entirely align with the commitment levels in the private market and the number of funds invested. The average LP makes 27.06 commitments in the private equity market. Public pension funds and private pension funds make the greatest number of commitments, while wealth managers and corporations make the lowest. Consistently, public pension funds emerge as the most active investors in our sample, investing in an average of 21 funds, followed by private pension funds with 8.8 funds. Despite having the largest LP counts, wealth managers, and corporations appear to be the least active, with average investments in 2 and 1.5 funds, respectively.

4.4.2 Regression Analysis

Fund sustainability orientation. Given that our outcome of interest, the proportion of SD ventures in a fund's portfolio, is a fraction bounded between zero and one, we use a fractional response model (FRM) as outlined by Papke and Wooldridge (1996, 2008). FRM's parameter estimation relies on a quasi-maximum likelihood method (QMLE), providing robust and reasonably efficient estimates within the framework of general linear models. The use of FRM facilitates easier interpretation as it estimates the predicted mean of our outcome variable, in contrast to standard logit or probit models that estimate the probability of either 0 or 1. Moreover, FRM holds an advantage over OLS models, particularly because the distribution of our outcome displays a significant pile-up at zero (Gallani et al. 2015; for a recent discussion about the use of FRM models, see Villadsen and Wulff 2021).[43]

Table 4.3 below presents the results of our regression analysis. The different models progressively introduce more control variables. Model 1 only includes the main predictor, *Fund backed by High WTP LPs*. In Model 2, we introduce time-invariant fund-level control variables. In Model 3, we add the vintage year to account for time trends. We code the starting vintage year of 1995 in our sample as 0, with subsequent vintage years represented as the difference from 1995. Model 4 instead codes each vintage year as year dummies. In Model 5, we add

[43] Using a simple OLS regression with the dependent variable multiplied by 100 would yield similar results, as indicated in the findings reported in Appendix C Table 4.11.

clusters by grouping vintage year and fund region. Finally, in Model 6, our preferred specification, we also add GP-level controls.

We find a positive and significant coefficient for our main variable of interest, *Fund backed by High WTP LPs*, suggesting that funds predominantly backed by high WTP LPs have, on average, more SD ventures in their portfolio than those with a majority of low WTP LPs. This finding is robust to the inclusion of a large set of control variables, although its magnitude reduces by around 40% moving from Model 1 to Model 6. Obtaining the predicted mean from Model 6, we find that funds with a majority of low WTP LPs have 5.34% of their portfolio comprised of SD ventures, compared to 6.06% for funds backed by high WTP LPs. Overall, our first hypothesis is supported. A fund predominantly backed by high WTP LPs exhibits an approximately 13.48% increase in the proportion of SD ventures compared to a fund with primarily low WTP LPs. This is an average effect across all funds in our sample. Below, we explore how the magnitude of this effect changes when including moderating variables as conjectured in Hypotheses 2 and 3.

As far as control variables are concerned, impact funds have a higher proportion of SD ventures in their portfolios, while a larger fund size is associated with a lower share of SD ventures. Additionally, being the first fund for a GP is associated with a higher sustainability orientation. For the fund type dummies, the baseline fund type is general interest VC funds. The effect for early-stage funds is negative, suggesting that funds targeting early-stage ventures have a lower share of SD ventures than general interest venture funds. Instead, later-stage and buyout funds have a higher share of SD ventures in the portfolio. Further, we find a negative association between *GP Fundraising Experience* and fund sustainability orientation, suggesting that as GPs gain fundraising expertise in the VC market, they invest in a lower share of SD ventures. This effect gradually diminishes as the squared term of *GP Fundraising Experience* is positive, albeit the coefficient is close to 0. Finally, we find a strong positive effect of GPs who had prior experiences in SD ventures by the time of a fund's vintage year. Accounting for this effect helps address the concerns about potential selection effects, ensuring that high WTP LPs are not merely choosing funds with GPs who already have prior investment experiences in SD ventures at the time of fundraising.

Table 4.3 Fund Sustainability Orientation

Dependent Variable: Fund Sustainability Orientation (Fraction of SD ventures in portfolio)						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fund backed by High WTP LPs	0.12***	0.09***	0.09***	0.07**	0.07**	0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Impact Fund		0.88***	0.84***	0.80***	0.80***	0.70***
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Fund Size		-0.00*	-0.00**	-0.00***	-0.00***	-0.00**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First Fund		0.12***	0.14***	0.16***	0.15***	0.12***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Comanaged Fund		0.01	0.02	-0.00	0.00	0.01
		(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Vintage (Trend)			0.02***			
			(0.00)			
GP Fundraising Experience						-0.03***
						(0.01)
GP Fundraising Experience - Squared						0.00***
						(0.00)
GP Had Experience in SD ventures						0.36***
						(0.04)
Early-Stage Fund		-0.01	-0.04	-0.05	-0.06	-0.07*
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Later-Stage Fund		0.11**	0.09	0.06	0.04	0.08
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Buyout Fund		0.11**	0.13**	0.11**	0.10*	0.14***
		(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Constant	-1.63***	-1.56***	-1.79***	-2.05***	-1.81***	-1.74***
	(0.02)	(0.04)	(0.05)	(0.21)	(0.36)	(0.35)
Observations	4,419	4,277	4,277	4,277	4,277	4,277
Fund Region FE		YES	YES	YES	YES	YES
Vintage Year FE				YES	YES	YES
Vintage Year * Fund Region FE					YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Misalignment of investment objectives. Our second hypothesis predicts that the positive effect of high WTP LPs on fund sustainability is more pronounced when a misalignment of investment objectives exists between the fund and its LPs. We introduce two moderating variables to test this hypothesis. First, we compare the effects across impact and conventional funds. We expect the positive effect of high WTP LPs on fund sustainability to be more pronounced in conventional funds that prioritize financial returns. Second, we expect the positive effect of high WTP LPs on fund sustainability to be stronger for funds located in countries with weaker social norms toward sustainability performance.

Table 4.4 below reports the regression results. Models 1 and 2 show a significant positive main effect of *Fund backed by High WTP LPs* and *Impact Fund,* respectively, with all controls as well as year, region, and year-region cluster fixed effects. Model 3 includes the interaction term between *Fund backed by High WTP LPs* and *Impact Fund.* For nonlinear models, it is essential to determine the size and significance of the interaction effect using marginal effects rather than regression coefficients (Ai and Norton 2003, Mize 2019). As noted by Ai and Norton (2003:129), "the interaction effect... cannot be evaluated simply by looking at the sign, magnitude, or statistical significance of the coefficient on the interaction term when the model is nonlinear." Additionally, illustrating the interaction effect is best achieved by plotting the predictions (Rönkkö et al. 2022).

Hence, we obtain the prediction of marginal effects from Model 3 and plot them in Figure 4.2. On average, impact funds have a higher proportion of SD ventures in their portfolio than conventional funds. Moreover, high WTP LPs has a significant positive effect (a relative 16.7% increase) on the portfolio of SD ventures in conventional funds. This effect is smaller (8.6%) and statistically insignificant in impact funds. This finding supports our argument that the misalignment of investment objectives between high WTP LPs and conventional funds amplifies the effect of high WTP LPs on fund sustainability orientation. However, the effect is muted in impact funds, whose investment objectives already prioritize SD ventures.

Model 4 shows the main effect of a fund being located in Europe, where social norms toward sustainability performance are higher than other regions of the world (e.g., Dyck et al.

2019). As expected, we found a positive main effect. As in previous models, Figure 4.3 shows the marginal effects from predictions in Model 5. The effect of high WTP is not present for funds located in Europe, but it is large and significant for funds located in the rest of the world (an increase of 30.4%).

Table 4.4 Misalignment of Investment Objective

Dependent Variable: Fund Sustainability Orientation (Fraction of SD ventures in portfolio)					
VARIABLES	(1)	(2)	(3)	(4)	(5)
Fund backed by High WTP LPs	0.10***		0.07**		0.09**
	(0.03)		(0.03)		(0.03)
Impact Fund		0.71***	0.71***	0.72***	0.69***
		(0.07)	(0.13)	(0.07)	(0.07)
Impact Fund × Fund backed by High WTP LPs			-0.02		
			(0.15)		
Fund located in Europe				0.17***	-0.09
				(0.04)	(0.12)
Fund located in Europe × Fund backed by High WTP LPs					-0.08
					(0.07)
Early-Stage Fund	-0.10**	-0.07*	-0.07*	-0.06*	-0.06*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Later-Stage Fund	0.08	0.09*	0.08	0.10*	0.08
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Buyout Fund	0.14**	0.15***	0.14***	0.16***	0.14***
	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Fund Size	-0.00***	-0.00**	-0.00**	-0.00**	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First Fund	0.13***	0.12***	0.12***	0.13***	0.12***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Comanaged Fund	0.03	0.02	0.01	0.01	0.02
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
GP Fundraising Experience	-0.03***	-0.03***	-0.03***	-0.02***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
GP Fundraising Experience - Squared	0.00***	0.00***	0.00***	0.00**	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GP Had Experience in SD ventures	0.42***	0.36***	0.36***	0.37***	0.36***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Constant	-1.76***	-1.69***	-1.74***	-2.13***	-1.61***
	(0.34)	(0.35)	(0.35)	(0.22)	(0.37)
Observations	4,277	4,277	4,277	4,277	4,277
Vintage Year FE	YES	YES	YES	YES	YES
Fund Region FE	YES	YES	YES	NO	NO
Vintage Year * Fund Region FE	YES	YES	YES	NO	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

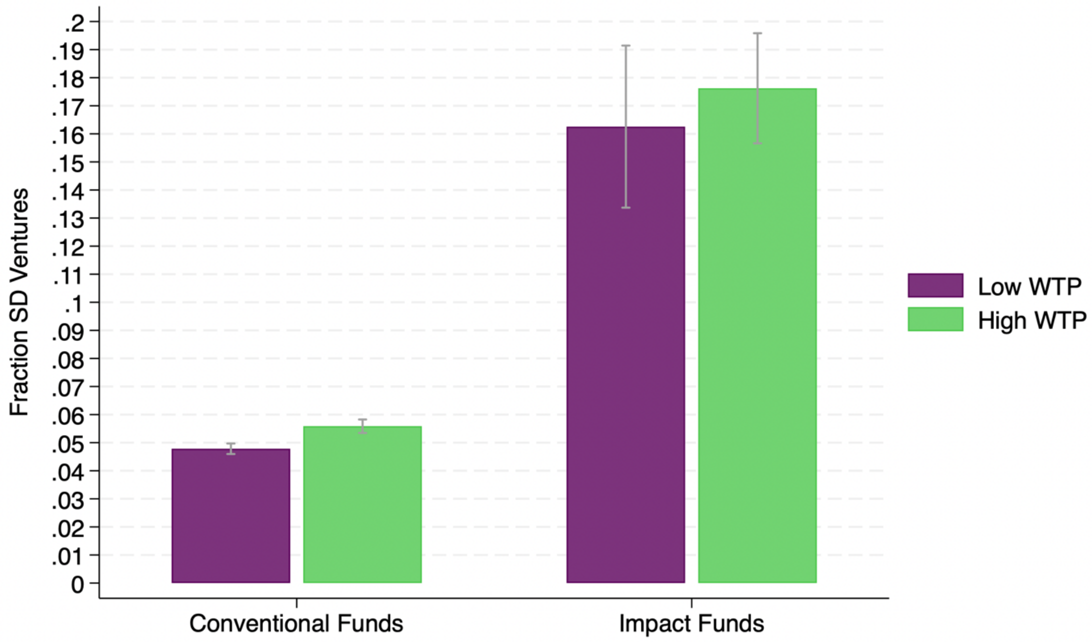

Figure 4.2 The Effect of High WTP LP on Fund Sustainability
in Impact vs. Conventional Funds

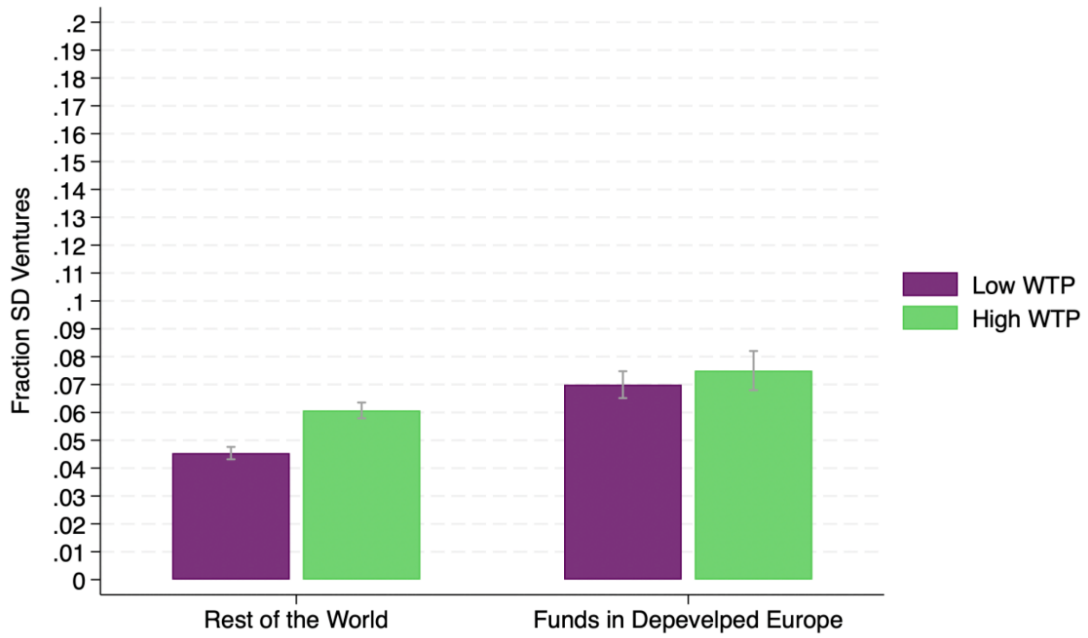

Figure 4.3 The Effect of High WTP on Fund Sustainability across Fund Regions

Fund malleability. We predict that LPs are more likely to be effective in influencing a fund's sustainability orientation if the fund is more responsive to demands from LPs. We thus expect that the effect of high WTP LPs on fund sustainability orientation will be more pronounced for funds managed by first-time and younger GPs. For this purpose, we explore the interaction effect of *Fund backed by High WTP LPs* with *First Fund* and *GP Fundraising Experience,* respectively. Table 4.5 reports the regression results and Figures 4.4 and 4.5 illustrate the predictions of marginal effects from Models 3 and 6. There is a positive main effect of *First Fund* and a negative effect of *GP Fundraising Experience* on the proportion of SD Ventures in the portfolio, as shown in Models 2 and 4, respectively. As illustrated in Figure 4.4, high WTP LPs have a significant positive effect on the portfolio of SD ventures. This effect is stronger in first-time funds than in non-first-time funds. Consistently, Figure 4.5 shows that the effect of high WTP LPs on fund sustainability is larger for younger GPs and diminishes in magnitude as GPs gain fundraising experiences. Overall, this renders support to our third hypothesis.

Table 4.5 Fund Adaptability

Dependent Variable: Fund Sustainability Orientation (Fraction of SD ventures in portfolio)						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fund backed by High WTP LPs	0.07**		0.08**	0.07**		0.08**
	(0.03)		(0.03)	(0.03)		(0.04)
First Fund		0.11**	0.12**	0.25***	0.11**	0.11**
		(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
First Fund × Fund backed by High WTP LPs			-0.03			
			(0.07)			
GP Fundraising Experience	-0.03***	-0.03***	-0.03***		-0.03***	-0.03***
	(0.00)	(0.01)	(0.01)		(0.01)	(0.01)
GP Fundraising Experience × Fund backed by High WTP LPs						-0.00
						(0.00)
Fund Size	-0.00**	-0.00**	-0.00**	-0.00***	-0.00**	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Comanaged Fund	0.06	0.05	0.04	-0.01	0.05	0.04
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
GP Fundraising Experience - Squared	0.00***	0.00***	0.00***		0.00***	0.00***
	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)
GP Had Experience in SD ventures	0.35***	0.36***	0.36***	0.31***	0.36***	0.36***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Early-Stage Fund	-0.06	-0.06*	-0.06	-0.05	-0.06*	-0.06
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Later-Stage Fund	0.07	0.08	0.07	0.07	0.08	0.07
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Buyout Fund	0.12**	0.13**	0.13**	0.14**	0.13**	0.13**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Constant	-1.64***	-1.68***	-1.73***	-1.89***	-1.68***	-1.75***
	(0.35)	(0.36)	(0.35)	(0.36)	(0.36)	(0.35)
Observations	4,130	4,130	4,130	4,130	4,130	4,130
Fund Region FE	YES	YES	YES	YES	YES	YES
Vintage Year FE	YES	YES	YES	YES	YES	YES
Vintage Year * Fund Region FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

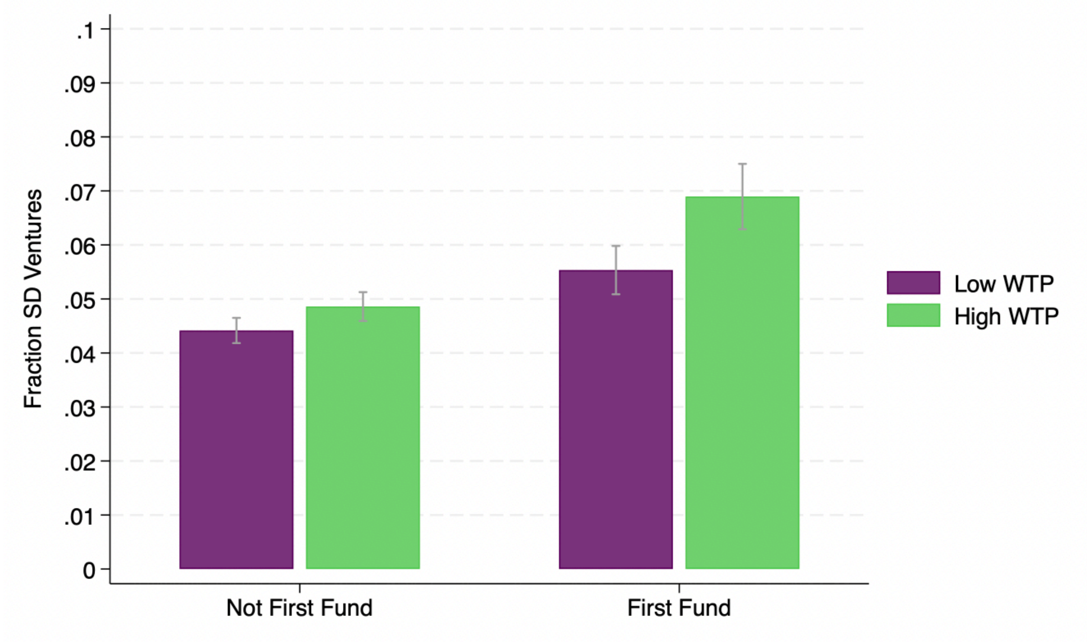

Figure 4.4 The Effect of High-WTP on Fund Sustainability in First vs. Non-First Funds

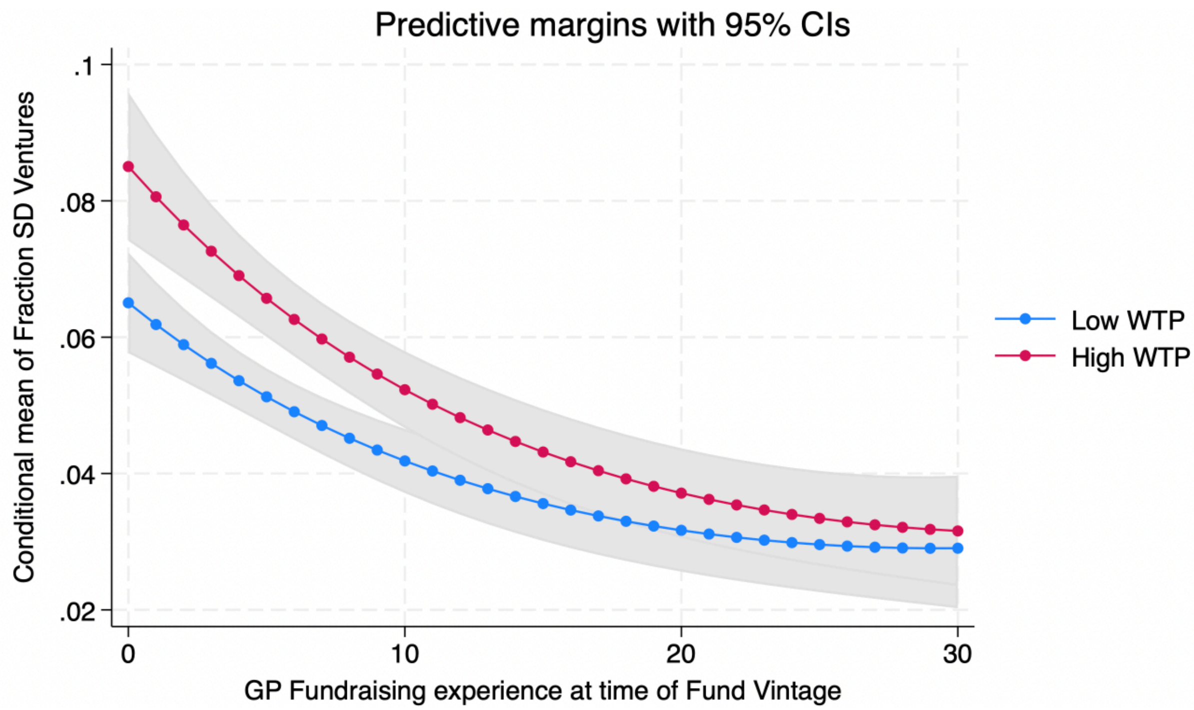

Figure 4.5 The Effect of High-WTP on Fund Sustainability across Range of GP Age

4.4.3 Robustness checks

To ensure the robustness of our findings, we performed a battery of robustness checks on different subsamples or using different measures for our key variables. A discussion of the findings is reported below, while all the regression tables appear in Appendix C.

*Alternative Samples***.** We replicated our analysis on two distinct subsamples. Firstly, in response to the potential concern that buyout funds, which are much larger in size and typically target established companies, might exhibit different investment styles compared to funds focusing on VC or growth equity, we excluded the 11% buyout funds from our sample. Notably, the significance and magnitude of our main analysis remained consistent.

Liquidated and Fully Invested Funds. We re-run our analysis on a subsample of 1,872 funds that are either already liquidated or fully invested. This approach helps alleviate concerns that closed funds might still retain the potential for investing in SD ventures at a later stage of a fund's lifecycle. For this purpose, we relaxed the upper limit of 2016 as the latest fund vintage year, as long as a fund is fully invested. This smaller sample of funds has a vintage year spanning from 1995 to 2022, with the average vintage being 2005. Across all models, the sign and significance of all variables remain largely consistent with our main analysis. Notably, the magnitude of our main predictor, *Fund backed by high WTP LPs*, becomes larger. The average share of SD ventures for funds with low WTP LPs is 4.3%, compared to 5.4% for funds with high WTP LPs, equivalent to about a 26% increase.

Alternative Measure of Impact Fund. Given the relatively small size of our impact fund sample, we constructed an alternative measure of funds' preference for impact investing. We used information from each GP's investment preferences as reported in Pitchbook, and created an alternative variable *Prefer Impact*, indicating funds managed by GPs with a stated preference for either "Seeks ESG investments," "Seeks Impact investments," or "Invests in MWBE (Minority and Women-owned)". 981 funds (22.2% of our sample) are identified as funds with a preference for investing in sustainability. Controlling for this measure helps address the potential effect of selection, i.e., high WTP LPs select funds that seek SD ventures.

We replicated our main regression analysis using this alternative measure of *Prefer Impact*. The results remain consistent. The coefficient of *Prefer Impact* is significant and positive, albeit smaller than that of *Impact Fund*. The average share of SD ventures for funds with low WTP LPs is 5.2%, compared to 6.2% for funds with high WTP LPs, equivalent to a 19% increase.

*Alternative Measure of Funds backed by high WTP LPs***.** Instead of using a 50% threshold for a fund with high WTP LPs, we replicated the previous analysis by directly using the fraction of LPs classified as high WTP in a fund. The results remain qualitatively similar to our main analysis. Going from having no high WTP LPs as investors to having all high WTP LPs changes the share of SD ventures from 5.3% to 6.2%, equivalent to a 16.0% increase.

Additional Analyses. An alternative explanation of the observed difference in sustainability portfolio between high and low WTP LPs is that a fund's sustainability orientation may simply reflect its risk profile, based on the assumption that SD ventures are inherently riskier than average ventures. To address this concern, we run the same analysis as above, but on a fund's share of ventures that got acquired, went public, and went out of business, respectively. If funds backed by high versus low WTP LPs differ in their risk profile, we should expect that there will be a difference in the share of liquidity events, including successful exits and out-of-business. We did not see any effect of being a fund backed by high WTP LPs on the share of ventures that experience successful exits in terms of M&A and IPO. However, having high WTP LPs is associated with a higher share of ventures that went out of business. Finally, we re-run our analyses on a fund's portfolio of environmentally-driven ventures, which constitute the majority of our SD ventures. Results remain qualitatively unchanged.

4.4.4 Instrumental Variable Approach

To account for potential selection effects, that is, funds that are expected to have a higher sustainability orientation attract more high WTP LPs at the time of fundraising, we introduce an instrumental variable specification using a two-stage model. This method complements the control for GP's experience with SD ventures that we include in all models.

In our study, an appropriate instrument must be related to the independent variable, the fraction of high WTP LPs investing in a fund, and remain exogenous to our outcome variable, fund sustainability orientation. For this purpose, we follow prior literature (e.g., Alvarez-Garrido and Dushnitsky 2016, Bottazzi et al. 2008) that leverages the local availability of selected characteristics as an instrument. In our context, we construct an instrument variable *Availability of Low WTP LP*, defined as the percentage of low WTP LPs investing in a fund's vintage year and country/State.[44] This instrument satisfies the relevance inclusion criterion, such that the share of low WTP LPs in a given market of a fund's fundraising year will be negatively correlated with a fund receiving capital commitments from high WTP LPs. Besides predictive power, this instrument also satisfies the criterion of exclusion restriction. While the actual matching of a fund and its LPs may be endogenous, the local availability of LPs is exogenous. Moreover, once a fund has established its LPs base, the availability of low WTP LPs in a market becomes irrelevant, since all that matters is the preference of LPs that were actually committing capital to a fund. Hence, it is reasonable to use the local availability of low WTP LPs as an instrumental variable.

In Table 4.6, we report findings from two-stage least square analyses using the continuous fraction of High WTP LPs in a given fund instead of a dummy, as in Table 4.3.[45] Models 1-2 include the full sample, with the control for impact funds; Models 3-4 include *Prefer Impact* (as explained in subsection 4.3.), serving as an alternative control for a fund's sustainability focus; Models 5-6 drop both funds categorized as impact and preferring impact, limiting the analysis to only conventional funds. As expected, across all models, the availability of low WTP LPs in a market-year predicts a lower share of high WTP LPs in a fund in the first-

[44] Since about 60% of our sample funds come from the United States, we measure this variable at the state level for U.S. funds. For funds based in other regions of the world, this variable is constructed at the country level.
[45] This is to avoid a "forbidden regression", as the first-stage regression in 2SLS requires a continuous endogenous variable. In appendix Table C13, we report findings in first-stage models using OLS with the dummy *Fund backed by High WTP LP* as the first-stage dependent variable.

stage regression. Moreover, *F*-statistic from first-stage predictions suggest that our instrument is sufficiently strong. Consistent among all stage-two models, we still observe a significant and positive effect of the fraction of high WTP LPs. Obtaining predictions from Model 6, that is, for conventional funds only, going from having no high WTP LPs as investors to having all high WTP LPs changes the share of SD ventures from 3.5% to 6.1%.[46] Results reported in Appendix C Table 4.19 using the dummy of High WTP LPs as the first-stage dependent variable yield similar results.[47]

[46] The magnitude of the effect derived from the instrumental variable specification is much larger than that obtained without instruments. This implies that our primary model specification (without instruments) likely does not suffer from omitted variable bias. More importantly, it suggests that the effect of high WTP LPs on fund sustainability orientation is more pronounced for funds sensitive to market availability of LPs with differing levels of WTP for social impact. These "complier" funds, presumably less experienced in fundraising and without inclination toward sustainability-related investments, are more prone to being influenced by high WTP LPs when determining the composition of SD ventures in their portfolio.

[47] We also report results for hypotheses 2 & 3 using IV specifications in Appendix C Table 4.20 and 4.21.

Table 4.6 Instrumental Variable Specification

First-stage DV: Fraction of High WTP LPs in Fund Second-stage DV: Fund Sustainability Orientation (Fraction of SD ventures in portfolio)						
VARIABLES	(1) First-stage	(2) Second-stage	(3) First-stage	(4) Second-stage	(5) First-stage	(6) Second-stage
Fraction High WTP LPs (predicted)		0.21**		0.23***		0.26***
		(0.09)		(0.09)		(0.10)
Availability of Low WTP LP	-0.93***		-0.94***		-0.96***	
(instrument)	(0.02)		(0.02)		(0.02)	
Impact	0.13***	0.68***				
	(0.03)	(0.07)				
Prefer Impact			-0.00	0.32***		
			(0.01)	(0.04)		
Fund Size	0.00	-0.00**	0.00	-0.00***	0.00***	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First Fund	0.01	0.12***	0.01	0.13***	0.01	0.10**
	(0.02)	(0.04)	(0.02)	(0.05)	(0.02)	(0.05)
Comanaged-Fund	0.05**	0.05	0.06**	0.02	0.04	-0.08
	(0.02)	(0.07)	(0.02)	(0.07)	(0.03)	(0.09)
GP Fundraising Experience	0.00	-0.03***	0.00	-0.03***	0.00	-0.02**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
GP Fundraising Experience - Squared	0.00	0.00***	0.00	0.00**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GP Had Experience in SD ventures	0.01	0.38***	0.02	0.40***	0.02	0.39***
	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)
Early-Stage Fund	-0.05***	-0.06	-0.05***	-0.11***	-0.04***	-0.07
	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)
Later-Stage Fund	0.04***	0.08	0.04***	0.05	0.06***	-0.00
	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.06)
Buyout Fund	0.05***	0.14**	0.05***	0.03	0.05**	0.10
	(0.01)	(0.05)	(0.02)	(0.06)	(0.02)	(0.08)
Constant	0.98***	-1.84***	0.99***	-2.03***	0.98***	-5.32***
	(0.02)	(0.33)	(0.02)	(0.25)	(0.03)	(0.25)
Observations	4,275	4,275	4,275	4,275	3,293	3,293
Vintage Year FE	YES	YES	YES	YES	YES	YES
Fund Region FE	YES	YES	YES	YES	YES	YES
Vintage Year * Fund Region FE	YES	YES	YES	YES	YES	YES
F-statistic	1078.26		1097.64		792.81	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.4.5 Mechanism Testing: LPs' Reinvestment Decision in GPs' Follow-on Funds

As previously discussed, LPs have two potential ways for influencing GPs to incorporate more sustainability-driven ventures into their fund portfolios. One direct mechanism involves private negotiations, wherein LPs apply governance pressure on GPs' decision-making process, advocating for the inclusion of ESG-related criteria when selecting startups. Although challenging to observe in second-hand data, recent survey studies (e.g., Botsari and Lang, 2021, Da Rin and Phalippou 2017, Krueger et al. 2020) have reported instances of this direct mechanism. Moreover, our empirical analyses of Hypotheses 2 and 3 provide evidence that is at least consistent with its implications. Below, we set out to investigate the indirect mechanism: LPs' reinvestment decisions.

Prior literature suggests that when GPs fail to meet LPs' expectations, LPs may opt not to reinvest in the subsequent fund managed by the same GP (Batt and Appelbaum 2021, Lerner et al. 2007). In our study, we aim to explore how the reinvestment decisions of high WTP LPs in the GPs' next fund may be influenced by the sustainability orientation of the current fund. If this indirect mechanism is at play, we should observe that high WTP LPs will be less likely to reinvest in the next fund of the same GPs if the sustainability performance of the current fund falls below their expectations.

For this purpose, we first identify all GPs with at least two consecutive funds within our sample, and treat each LP-fund dyad as a unique observation. That is, for each fund, we have distinct observations for each LP participating in it. For each observation, we code each LP's WTP for social impact, where 1 represents high WTP and 0 otherwise. To measure the current fund's sustainability performance, in addition to the absolute share of SD ventures in the portfolio, we also construct the variable *Share SD Below Average*. This is a dummy indicator for funds whose share of SD ventures in the portfolio is lower than that of funds with the same vintage year and location.[48] The interaction term between a fund's sustainability performance and LP high WTP is our main variable of interest, allowing us to compare the likelihood of reinvestment between high versus low WTP LPs, contingent on the fund's sustainability performance. We further include other fund- and LP-level control variables, such

[48] For funds located in the United States, the location is specified at the state level. For funds located elsewere, the location is identified at the country level.

as fund financial performance (measured by internal rate of return, IRR), co-location of the current fund with its LP, total number of LPs in the next fund, as well as LPs' overall percentage of commitments in VC and PE within the alternative asset class. Given that the dependent variable is binary (1 indicating LP reinvestment in the next fund, 0 otherwise), we use a logit specification, with robust standard errors. Table 4.7 presents the results of this analysis.

Models 1-3 present results using the fund-level Share of SD ventures as the predictor, whereas Models 4-6 use the dummy variable *Share SD Below Average.* Across these models, high WTP LPs generally exhibit a higher likelihood of reinvesting in the next fund of a GP, potentially due to the larger capital at their disposal, as is often the case with high WTP LPs such as public pension funds. Interestingly, we do not observe a main effect of fund sustainability performance on LPs' reinvestment decisions, except in Model 4. When the fund-level share of SD ventures is below average, LPs are less likely to reinvest in the next fund. However, this coefficient becomes insignificant once control variables are introduced. As in previous non-linear models, we assess the effect of the interaction term by plotting the marginal effects from Models 3 and 6, respectively.

Figure 4.6 illustrates the predicted likelihood of reinvestment by high versus low WTP LPs, contingent on the share of SD ventures in the current fund. Here we do not observe a discernible difference in trend between high and low WTPs. As the share of SD ventures increases, there is a slight drop of reinvestment probability for both high and low WTP LPs. In Figure 4.7, the probability of reinvestment is differentiated between funds with sustainability performance below or above average. Notably, for funds with above average sustainability performance, high WTP LPs exhibit a higher likelihood of reinvestment compared to low WTP LPs. However, high WTP LPs are also more likely to reinvest even when the fund's sustainability performance is below average, although to a lesser extent. These pieces of evidence provide little support to the conjecture that high WTP LPs' reinvestment decisions are contingent upon fund sustainability performance.

As indicated in Table 4.7, it is apparent that other control variables serve as stronger predictors of reinvestment decisions. For instance, fund IRR is positively correlated with reinvestment decisions, although the coefficient is very small and becomes insignificant when additional control variables are included. One consistent predictor of reinvestment decisions is the co-location between LPs and GPs, suggesting that most LPs are inclined to commit capital to local funds (Hochberg and Rauh 2013).

Overall, our analysis does not provide evidence supporting the indirect mechanism of LPs' influence on GPs through reinvestment decisions in our context. We conjecture that LPs' influence on fund sustainability orientation primarily occurs through private negotiations, governance mechanisms, and ongoing monitoring.

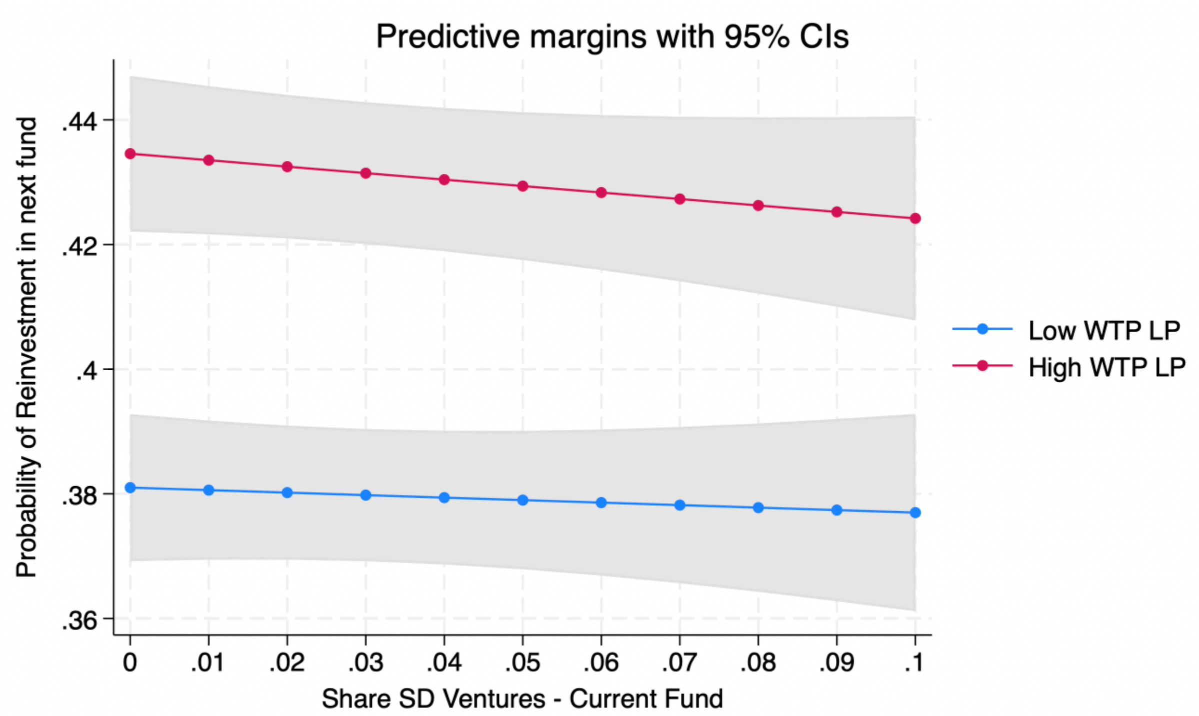

Figure 4.6 Probability of Reinvestment by by High versus Low WTP LPs

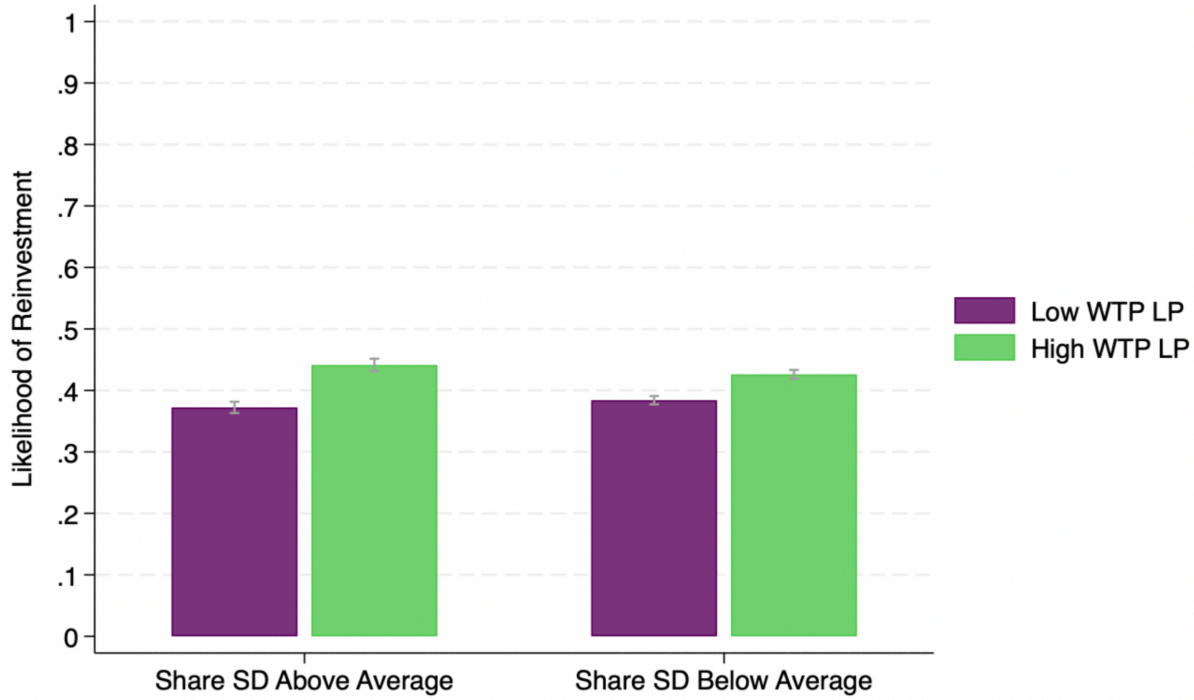

Figure 4.7 Probability of Reinvestment by Sustainability Performance

Table 4.7 LPs' Reinvestment Decisions

Dependent variable: LPs' reinvestment in GPs' next fund						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fund Share SD	-0.34	-0.35	-0.20			
	(0.24)	(0.31)	(0.42)			
LP High WTP	0.22***	0.18***	0.19***	0.22***	0.18***	0.27***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)
LP High WTP × Fund Share SD			-0.29			
			(0.55)			
Share SD Below Average				-0.24***	-0.01	0.06
				(0.04)	(0.04)	(0.06)
LP High WTP × Share SD Below Average						-0.13
						(0.08)
IRR	0.00***	-0.00	-0.00	0.00***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GP-LP-colocation		0.39***	0.39***		0.38***	0.38***
		(0.06)	(0.06)		(0.06)	(0.06)
Impact Fund		-0.29	-0.28		-0.39	-0.40
		(0.31)	(0.31)		(0.29)	(0.30)
Early Stage Fund		0.42***	0.42***		0.42***	0.42***
		(0.07)	(0.07)		(0.07)	(0.07)
Later Stage Fund		-0.31***	-0.31***		-0.31***	-0.31***
		(0.07)	(0.07)		(0.07)	(0.07)
Buyout Fund		-0.84***	-0.84***		-0.84***	-0.85***
		(0.05)	(0.05)		(0.05)	(0.05)
LP Percent Commit In VC&PE		-0.70***	-0.70***		-0.70***	-0.70***
		(0.12)	(0.12)		(0.12)	(0.12)
Number LP next Fund		0.02***	0.02***		0.02***	0.02***
		(0.00)	(0.00)		(0.00)	(0.00)
Constant	-0.51***	-0.97***	-0.97***	-0.37***	-0.97***	-1.01***
	(0.03)	(0.21)	(0.21)	(0.04)	(0.21)	(0.21)
Observations	13,330	13,327	13,327	13,330	13,327	13,327
Fund Region FE		YES	YES		YES	YES
Vintage Year FE		YES	YES		YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.5 Discussion

This paper presents a comprehensive analysis of the role played by LPs in shaping the investment strategies of VC funds, with a focus on the composition of SD ventures within their portfolios. Our findings suggest that the presence of high WTP LPs increases the inclusion of SD ventures in a fund's investment portfolios. This effect is particularly pronounced in funds without a stated preference for impact investing, in funds located in countries with weak sustainability norms, as well as in funds managed by first-time and young GPs. We employ an instrumental-variable approach to show that the effect is likely to be driven by pressures exerted by LPs on GPs, rather than by selection effect. We also find scant evidence that pressures are linked to subsequent reinvestment decisions, suggesting that LPs use their influence at the moment they invest in the fund or in subsequent contact and negotiations with GPs regarding investment portfolio decisions.

The main implication of our results is that LPs' preferences for sustainability are a significant driver of sustainable investment in private markets. From the perspective of portfolio companies, our results suggest that SD ventures can rely not only on impact funds, but they can also improve their funding prospects by considering conventional VC funds that are backed by capital commitments from high WTP LPs. These investors could offer SD ventures a variety of benefits, supporting their sustainability mission, including lower capital costs, increased investor patience with innovative business model developments, and better guidance toward alignment of financial performance and sustainability.

Future work could extend our research in several ways. Firstly, our study does not delve into the motivations driving investors' preferences for sustainability, nor does it explore the point at which a potential tradeoff between portfolio sustainability and performance emerges (Gantchev et al. 2024). Future research in the private equity market could further explore how a balance must be struck between maintaining a sustainable portfolio and optimizing financial performance. Secondly, our current study provides only indirect evidence of contracting, negotations, monitoring, and other mechanisms that LPs can employ to exert pressure on GPs. Collecting first-hand evidence of such mechanisms would represent a crucial area for further research. Another interesting avenue for future work is to explore the broader role of LPs in shaping fund investment styles, extending beyond sustainability orientation. For example, public pension funds have been found to exhibit a strong home-state bias in private equity (Hochberg and Rauh 2013), despite their in-state investments achieving much lower performance than out-of-state investments. One could study whether this preference manifests in VC funds' portfolio choice of local startups.

4.6 Appendix A: Additional Sample Characteristics

4.6.1 Sample of Funds

Table 4.8 Sampling of Funds

	Dropped	Remained
Total number of funds that had equity investments in Pitchbook		25,325
Funds managed by Investors whose primary strategy does not center around venture capital (VC) or private equity (PE)	2,533	22,792
Funds managed by investors with special mandates	55	22,737
SBIC Funds	170	22,567
Funds that had solely non-VC-related deals	12	22,555
Funds' vintage year before 1995 or after 2016	11,302	11,253
Canceled funds	5	11,248
Funds that are still open	9	11,239
Funds' portfolio of VC-backed companies smaller than 3	3,051	8,188
Funds that do not have LP information	3,769	4,419

4.6.2 Sample of Portfolio Ventures

Among the 45,872 portfolio ventures invested in by our sample of funds, we identified 2,675 (5.83%) as sustainability-driven ventures. The majority of these ventures (n = 2,366) are environmentally driven, with only 365 ventures categorized as socially driven. Figure 4.7 below illustrates the supply of SD ventures in terms of the number and percentage of new sustainability-driven ventures based on their founding year between 1995 and 2019. On average, there is an increase in the supply of SD ventures.

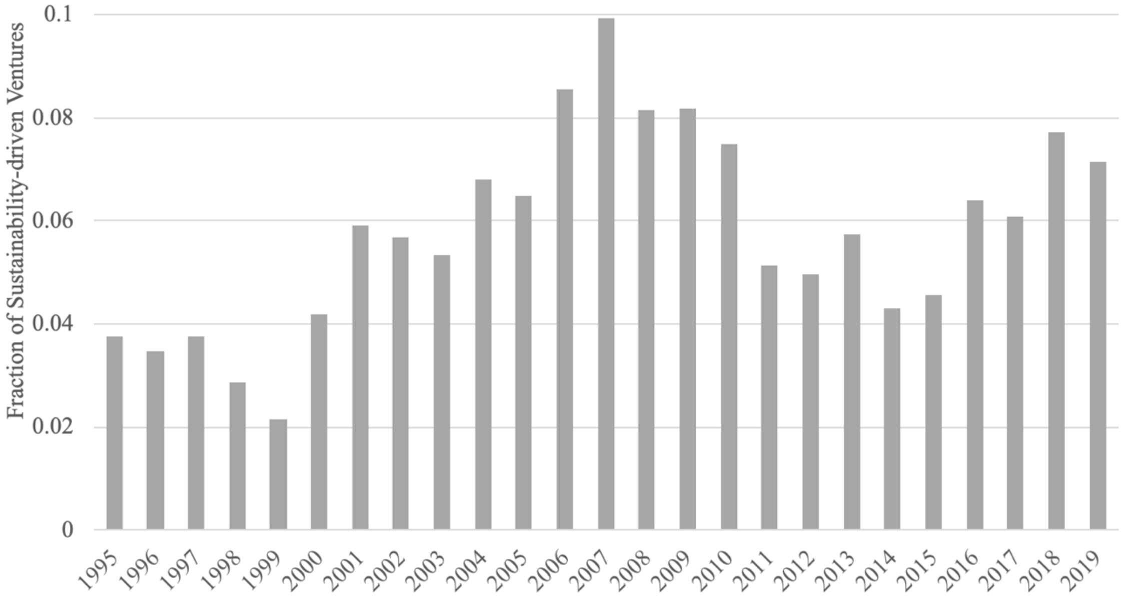

Figure 4.8 Sustainability-driven Ventures by Founding Year

4.6.3 Sample of LPs

Table 4.8 below provides a summary of our sample of LPs categorized by type. Following the approach outlined by Barber et al. (2021), we organized Pitchbook's classification of LP type into nine broad categories. Specifically, we combined economic development agencies and government agencies into the category of development organizations. Consistent with conventions, insurance companies and banks were grouped together as financial institutions. Together with foundation and public pension funds, these LP types are defined as exhibiting a high willingness to pay (WTP) for social impact. On the other hand, for low WTP LPs, corporate pension and union pension funds were combined into the category of private pension funds. Additionally, we classified various investment agencies, asset management firms, and family offices into the wealth manager category. The remaining category, institutional, served as a residual group, encompassing all other LPs not falling into the aforementioned types.

Table 4.9 Categorization and Breakdown of LP types

WTP	Grouped LP Type	Pitchbook's LP Type	N	%
High	Foundation	Foundation	676	11.01
	Public Pension Fund	Public Pension Fund	317	5.16
	Development organization	Economic Development Agency	127	2.07
		Government Agency	80	1.30
	Financial Institution	Insurance Company	416	6.77
		Banking Institution	223	3.63
Low	Private Pension Fund	Corporate Pension	696	11.33
		Union Pension Fund	153	2.49
	Corporation	Corporation	996	16.22
	Endowment	Endowment	189	3.08
	Wealth Manager	High-net-worth investor	905	14.73
		Private Investment Fund	203	3.31
		Money Management Firm	115	1.87
		Investment Advisor	84	1.37
		Wealth Management Firm	74	1.20
		Family Office (Single)	63	1.03
		Family Office (Multi)	42	0.68
	Institutional	Direct Investment	440	7.16
		Fund of Funds	273	4.44
		Sovereign Wealth Fund	24	0.39
		Real Estate Investment Company	21	0.34
		Secondary LP	11	0.18
		Other Limited Partner	8	0.13
		University (Non-Endowment)	5	0.08
		Mutual Fund Company	1	0.02
Total			6,142	100

4.6.4 LP commitments in impact funds

We validate the categorization of high vs. low WTP LPs by analyzing LPs' capital commitments to impact funds. Drawing on observations from Barber et al. (2021), we expect to observe that high WTP LPs invest in more impact funds compared to low WTP LPs. To assess this, we considered the universe of each fund-LP dyad reported in Pitchbook, comprising 11,052 unique funds and 16,642 LPs. Within this dataset, 372 funds are identified as impact funds based on the list of 275 impact investors compiled by Cole et al. (2022). We then computed both the average number and proportion of impact funds committed to by each LP. The combined averages for each LP type are reported in Table 4.12 below.

Overall, the categorization of high vs. low WTP LP from Barber et al. (2021) is supported. High-WTP LPs have committed capital to a greater number of impact funds compared to low-WTP LPs. There is also, on average, a higher percentage allocation to impact funds among high WTP LPs[49].

Table 4.10 LP Commitments in Impact Funds by Type

WTP	**LP Type**	**Number of Impact Funds**	**% of Impact Funds**
High	Development Organization	0.44	6.29
	Foundation	0.34	8.91
	Financial Institution	0.26	6.63
	Public Pension Fund	0.24	1.62
Low	Institutional	0.17	2.90
	Endowment	0.10	2.10
	Wealth Manager	0.08	4.48
	Corporation	0.05	2.54
	Private Pension Fund	0.04	1.62

[49] With the exception of public pension funds, whose percentage allocation to impact funds is relatively low. This can be attributed to the fact that public pension funds invest in a significantly higher total number of funds compared to other investor types.

4.7 Appendix B: Keywords list to match sustainability-driven ventures

ENVIRONMENTAL ISSUES	SOCIAL ISSUES
‘agri-tech’, ‘agritech’	‘affordable home’, ‘affordable-home’, ‘affordable homes’
‘alternative protein’, ‘alt protein’	‘base of the pyramid’, ‘base-of-the-pyramid’
‘animal free’, ‘animal-free’	‘bottom of the pyramid’, ‘bottom-of-the-pyramid’
‘animal friendly’, ‘animal-friendly’	‘charity’, ‘charities’
‘bio/agricultural’, ‘bio agro’, ‘bio-agro’	‘child labour’, ‘child labor’, ‘child-labour’, ‘child-labor’
‘bio-based’, ‘bio based’	‘community invest’, ‘community-invest’
‘biodegradable’	‘community development’, ‘community-development’
‘biodiversity’, ‘bio-diversity’, ‘bio diversity’	‘CSR’, ‘C.S.R.’
‘bioeconomy’, ‘bio-economy’, ‘bio economy’	‘DEI’, ‘D.E.I.’
‘bioenergy’, ‘bio-energy’, ‘bio energy’	‘disadvantaged’
‘bio fuel’, ‘biogas’, ‘bio-fuel’	‘donate’, ‘donation’
‘biomass’, ‘bio-mass’	‘double bottom line’, ‘double-bottom-line’
‘biomarine’	‘dual bottom line’, ‘dual-bottom-line’
‘bioplastics’	‘equality’
‘bioproducts’, ‘bio-products’	‘ethical’, ‘ethical-’
‘bio-remediation’, ‘bio remediation’	‘ethically’, ‘ethically-’
‘bio-sustainable’, ‘bio-sustainability’	‘ethics’
‘carbon’	‘fair trade’, ‘fair-trade’, ‘fairtrade’
‘chemical free’, ‘chemical-free’	‘human right’, ‘human-right’
‘CCUS’	‘hunger’
‘circular economy’, ‘circular-economy’	‘impact investing, ‘impact-investing’, ‘impact investment’
‘clean air’	‘impoverished’
‘clean tech’, ‘cleantech’, ‘clean-tech’	‘inclusion’
‘clean water’, ‘clean-water’	‘inclusive’
‘climate change’, ‘climate-change’	‘inclusively’
‘conservation’	‘indigenous’
‘cruelty-free’	‘invest ethical’
‘deforestation’	‘investing ethical’
‘e-waste’	‘local supplier’, ‘local-supplier’
‘earth’, ‘earth-’	‘minority community’, ‘minority-community’
‘energy conservation’, ‘energy-conservation’	‘minority owned’, ‘minority-owned’
‘energy efficiency’, ‘energy-efficiency’, ‘energy efficient’, ‘energy-efficient’	‘missing middle’, ‘missing-middle’
‘eco-’, ‘ecological’, ‘ecological-’, ‘ecologically’, ‘ecologically-’	‘mission driven’, ‘mission-driven’
‘environmental’, ‘environmental-’, ‘environmentally’, ‘environmentally-’	‘mission investing’, ‘mission-investing’
‘forest protection’	‘mission related’, ‘mission-related’
‘fossil fuel-free’	‘modern slavery’, “modern-slavery’
‘green building’, ‘green-building’	‘modern slave’, ‘modern-slave’
‘green energy’, ‘green-energy’	‘nonprofit’, ‘non-profit’, ‘not-for-profit’, ‘not for profit’
‘green focused’, ‘green-focused’	‘poverty’
‘greenhouse’	‘purpose driven’, ‘purpose-driven’
‘green finance’, ‘green-finance’	‘responsible business’, ‘responsible-business’
‘GHG’, ‘G.H.G.’	‘responsible investment’, ‘responsible-investment’
‘less waste’	‘rural women’, ‘rural-women’
‘low carbon’, ‘low-carbon’, ‘lower carbon’, ‘lower-carbon’	‘SDG’, ‘S.D.G.’, ‘SDGs’
‘natural environment’, ‘natural-environment’	‘slave-free’
‘natural ingredient’, ‘natural-ingredient’	‘SRI’, ‘S.R.I.’
‘natural resource’, ‘natural-resource’	‘social challenge’, ‘social-challenge’
‘non-plastic’	‘social finance’, ‘social-finance’
‘ocean-friendly’	‘social good’, ‘social-good’
‘organic’, ‘organic-’	‘social impact’, ‘social-impact’
‘planetary boundary’, ‘planetary-boundary’, ‘planetary boundaries’	‘social objective’
‘plant-based’, ‘plant based’	‘social responsibility’, ‘social-responsibility’
‘plastic-free’, ‘plastic free’	‘socially conscious’, ‘socially-conscious’
‘pollution control’	‘social entrepreneurship’, ‘social-entrepreneurship’
‘recycling’, ‘recyclable’, ‘recycled’	‘social entrepreneur’, ‘social-entrepreneur’
‘regenerative’	‘socially motivated’, ‘socially-motivated’
‘renewable’, ‘renewables’	‘socially responsible’, ‘socially-responsible’
‘reusable’	‘socially sustainable’, ‘socially-sustainable’
‘soil remediation’, ‘soil-remediation’	‘sustainable development’, ‘sustainable-development”
‘solar’	‘sustainable economic development’
‘sustainable agriculture’, ‘sustainable-agriculture’	‘sustainable farming’, ‘sustainable-farming’
‘sustainable business practice’	‘sustainable investment’, ‘sustainable-investment’
‘sustainable fishing’, ‘sustainable-fishing’	‘sustainable investing’, ‘sustainable-investing’
‘sustainable forestry’, ‘sustainable-forestry’, ‘sustainable forest management’	‘tribe’
‘sustainable manufacturing’,	‘triple bottom line’, ‘triple-bottom-line’
‘sustainable packaging’,	‘women business’, ‘women-business’
‘sustainable property’, ‘sustainable-property’	‘women owned’, ‘women-owned’
‘sustainable water’, ‘sustainable-water’	
‘vegan’, ‘vegan-’, ‘vegetarian’	
‘virgin resource’, ‘virgin-resource’	
‘waste reduction’, ‘waste-reduction’	
‘water efficient’, ‘water-efficient’, ‘water efficiency’, ‘water-efficiency’	
‘water footprint’, ‘water-footprint’	
‘water conservation’, ‘water-conservation’	
‘wind farm’, ‘wind-farm’, ‘wind farms’	

Notes: Case insensitive; variations with suffixes to the phrase are also matched.

4.8 Appendix C: Additional Analysis

Table 4.11 Hypothesis 1 using OLS regression

Dependent Variable: Fund Sustainability Orientation (100 * Share SD Ventures)						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fund backed by High WTP LPs	1.40***	0.91***	0.86**	0.69**	0.66*	0.64*
	(0.36)	(0.34)	(0.34)	(0.34)	(0.34)	(0.34)
Impact Fund		17.91***	17.49***	17.05***	16.92***	15.72***
		(2.10)	(2.11)	(2.08)	(2.07)	(2.04)
Fund Size		-0.00**	-0.00***	-0.00***	-0.00***	-0.00***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First Fund		1.46***	1.59***	1.76***	1.72***	1.47***
		(0.42)	(0.42)	(0.42)	(0.42)	(0.51)
Comanaged Fund		0.13	0.14	-0.09	-0.08	-0.18
		(0.87)	(0.87)	(0.88)	(0.89)	(0.91)
Vintage (Trend)			0.19***			
			(0.02)			
GP Fundraising Experience						-0.27***
						(0.06)
GP Fundraising Experience - Squared						0.00**
						(0.00)
GP Had Experience in SD ventures						4.43***
						(0.47)
Early-Stage Fund		-0.09	-0.47	-0.60	-0.67	-0.70*
		(0.41)	(0.41)	(0.41)	(0.42)	(0.41)
Later-Stage Fund		1.37**	1.09	0.82	0.67	1.08
		(0.67)	(0.67)	(0.67)	(0.67)	(0.66)
Buyout Fund		1.35**	1.48**	1.35**	1.24*	1.75***
		(0.67)	(0.66)	(0.66)	(0.66)	(0.65)
Constant	5.17***	6.20***	3.89***	2.90***	3.44	4.30
	(0.22)	(0.51)	(0.57)	(1.04)	(3.54)	(3.38)
Observations	4,419	4,277	4,277	4,277	4,277	4,277
R-squared	0.00	0.10	0.11	0.13	0.14	0.17
Fund Region FE		YES	YES	YES	YES	YES
Vintage Year FE				YES	YES	YES
Vintage Year * Fund Region FE					YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.12 Hypothesis 1 in a subsample without buyout funds

Dependent Variable: Fund Sustainability Orientation (Fraction of SD ventures in portfolio)						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fund backed by High WTP LPs	0.13***	0.09***	0.09***	0.08**	0.07**	0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Impact Fund		0.84***	0.81***	0.77***	0.76***	0.67***
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Fund Size		-0.00***	-0.00***	-0.00***	-0.00***	-0.00**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First Fund		0.08**	0.09**	0.11***	0.11***	0.09*
		(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Comanaged Fund		0.00	0.01	-0.01	0.00	-0.01
		(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
Vintage (Trend)			0.02***			
			(0.00)			
GP Fundraising Experience						-0.03***
						(0.01)
GP Fundraising Experience - Squared						0.00***
						(0.00)
GP Had Experience in SD ventures						0.37***
						(0.04)
Early-Stage Fund		-0.01	-0.04	-0.06	-0.06*	-0.07*
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Later-Stage Fund		0.13**	0.11**	0.08	0.07	0.11**
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Constant	-1.63***	-1.54***	-1.77***	-2.02***	-1.77***	-1.71***
	(0.02)	(0.04)	(0.05)	(0.21)	(0.36)	(0.35)
Observations	3,919	3,791	3,791	3,791	3,791	3,791
Fund Region FE		YES	YES	YES	YES	YES
Vintage Year FE				YES	YES	YES
Vintage Year * Fund Region FE					YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.13 Hypothesis 1 with a sample of liquidated and fully invested funds

Dependent Variable: Fund Sustainability Orientation (Fraction of SD ventures in portfolio)						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fund backed by High WTP LPs	0.14***	0.14***	0.12**	0.12**	0.13***	0.12**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Impact Fund		0.97***	0.88***	0.87***	0.86***	0.73***
		(0.12)	(0.12)	(0.11)	(0.11)	(0.12)
Fund Size		-0.00	-0.00	-0.00	-0.00*	-0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First Fund		0.06	0.09	0.08	0.07	0.00
		(0.06)	(0.06)	(0.05)	(0.05)	(0.07)
Comanaged Fund		-0.01	-0.04	-0.02	0.00	0.05
		(0.09)	(0.10)	(0.10)	(0.10)	(0.11)
Vintage (Trend)			0.02***			
			(0.00)			
GP Fundraising Experience						-0.03**
						(0.01)
GP Fundraising Experience - Squared						0.00
						(0.00)
GP Had Experience in SD ventures						0.37***
						(0.06)
Early-Stage Fund		0.05	-0.03	-0.01	-0.02	-0.05
		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Later-Stage Fund		0.14*	0.06	0.06	0.01	0.04
		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Buyout Fund		0.10	0.09	0.07	0.05	0.07
		(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Constant	-1.73***	-1.63***	-1.87***	-1.99***	-1.81***	-1.69***
	(0.04)	(0.06)	(0.06)	(0.22)	(0.37)	(0.36)
Observations	1,872	1,832	1,832	1,832	1,832	1,832
Fund Region FE		YES	YES	YES	YES	YES
Vintage Year FE				YES	YES	YES
Vintage Year * Fund Region FE					YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.14 Hypothesis 2 with a sample of liquidated and fully invested funds

Dependent Variable: Fund Sustainability Orientation					
VARIABLES	(1)	(2)	(3)	(4)	(5)
Fund backed by High WTP LPs	0.14***		0.12**		0.12**
	(0.05)		(0.05)		(0.06)
Impact Fund		0.74***	0.70***	0.75***	0.73***
		(0.12)	(0.22)	(0.11)	(0.11)
Impact Fund × Fund backed by High WTP LPs			0.04		
			(0.26)		
Fund located in EU				0.16***	0.20***
				(0.05)	(0.07)
Fund located in EU × Fund backed by High WTP LPs					-0.04
					(0.10)
Early-Stage Fund	-0.11*	-0.06	-0.05	-0.05	-0.04
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Later-Stage Fund	0.06	0.06	0.05	0.10	0.09
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Buyout Fund	0.05	0.08	0.07	0.10	0.09
	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)
Fund Size	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First Fund	-0.00	0.00	0.00	0.02	0.02
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Comanaged Fund	0.01	0.06	0.05	0.02	0.01
	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)
GP Fundraising Experience	-0.04***	-0.03**	-0.03**	-0.02**	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
GP Fundraising Experience - Squared	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GP Had Experience in SD ventures	0.43***	0.37***	0.37***	0.37***	0.37***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Constant	-1.67***	-1.59***	-1.69***	-1.96***	-2.05***
	(0.35)	(0.37)	(0.36)	(0.23)	(0.23)
Observations	1,832	1,832	1,832	1,832	1,832
Vintage Year FE	YES	YES	YES	YES	YES
Fund Region FE	YES	YES	YES	NO	NO
Vintage Year * Fund Region FE	YES	YES	YES	NO	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

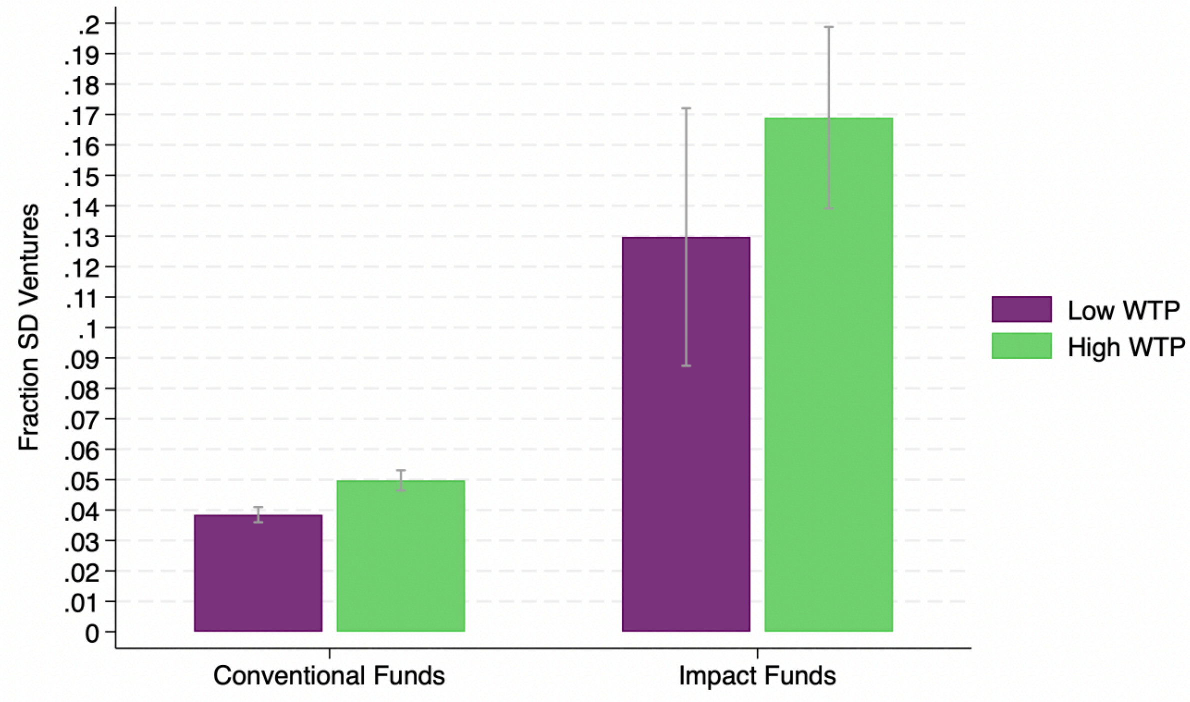

Figure 4.9 The Effect of High WTP LP on Fund Sustainability in Impact versus Conventional Funds (Sample of liquidated and fully invested funds)

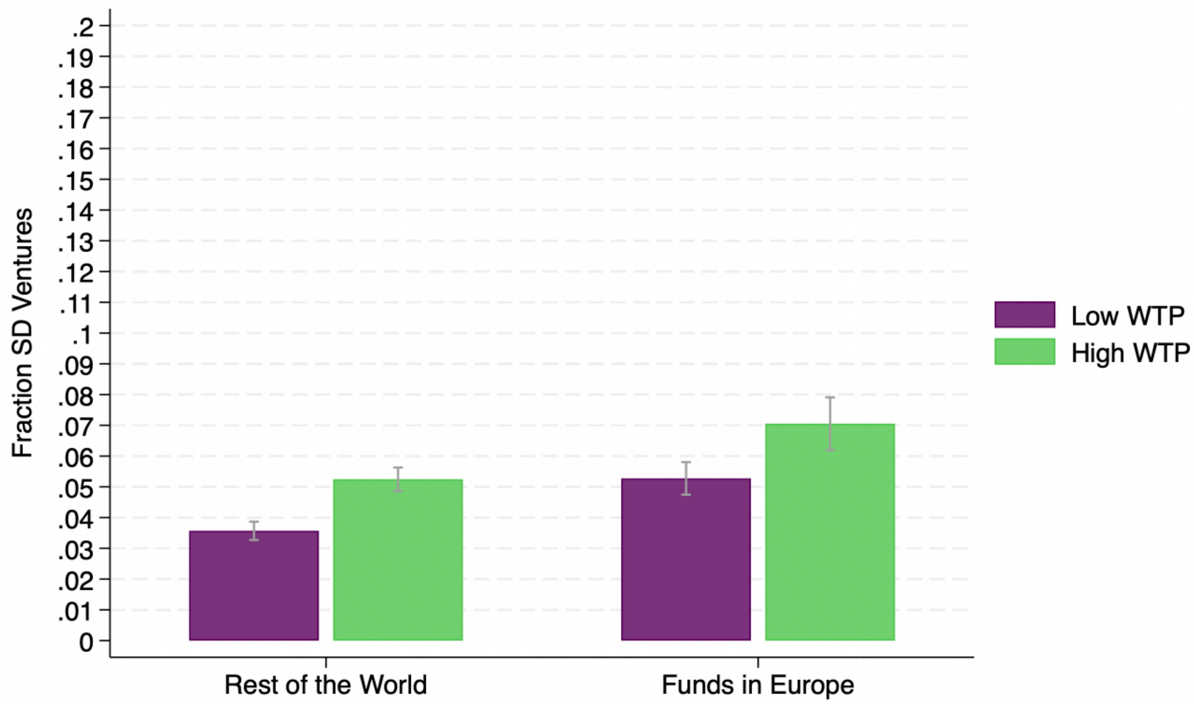

Figure 4.10 The Effect of High WTP LP on Fund Sustainability across Fund Region

Table 4.15 Hypothesis 3 with a sample of liquidated and fully invested funds

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fund backed by High WTP LPs	0.12**		0.17***	0.13***		0.10
	(0.05)		(0.06)	(0.05)		(0.07)
First Fund		0.02	0.11	0.17***	0.02	0.01
		(0.08)	(0.09)	(0.06)	(0.08)	(0.08)
First Fund × Fund backed by High WTP LPs			-0.17			
			(0.11)			
GP Fundraising Experience	-0.03***	-0.03**	-0.03**		-0.03**	-0.03**
	(0.01)	(0.01)	(0.01)		(0.01)	(0.01)
GP Fundraising Experience × Fund backed by High WTP LPs						0.00
						(0.01)
Fund Size	-0.00	-0.00	-0.00	-0.00**	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Comanaged Fund	0.05	0.06	0.05	0.05	0.06	0.05
	(0.10)	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)
Impact Fund	0.73***	0.74***	0.73***	0.79***	0.74***	0.73***
	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)
Early-Stage Fund	-0.05	-0.06	-0.05	-0.02	-0.06	-0.05
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Later-Stage Fund	0.04	0.06	0.04	0.04	0.06	0.04
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Buyout Fund	0.07	0.08	0.07	0.09	0.08	0.07
	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)
GP Fundraising Experience - Squared	0.00	0.00	0.00		0.00	0.00
	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)
GP Had Experience in SD ventures	0.37***	0.37***	0.37***	0.31***	0.37***	0.37***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Constant	-1.69***	-1.60***	-1.68***	-1.88***	-1.60***	-1.68***
	(0.36)	(0.37)	(0.37)	(0.37)	(0.37)	(0.36)
Observations	1,833	1,833	1,833	1,833	1,833	1,833
Fund Region FE	YES	YES	YES	YES	YES	YES
Vintage Year FE	YES	YES	YES	YES	YES	YES
Vintage Year * Fund Region FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

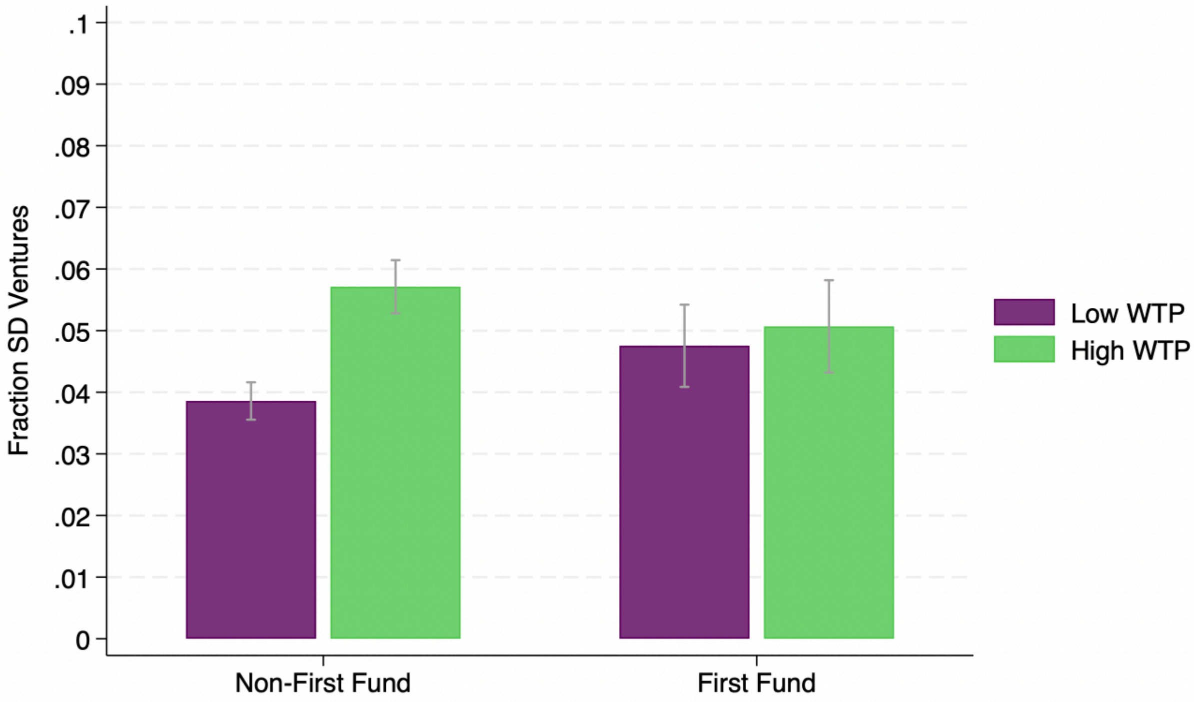

Figure 4.11 The Effect of High WTP LP on Fund Sustainability in First versus Non-First Funds (Sample of liquidated and fully invested funds)

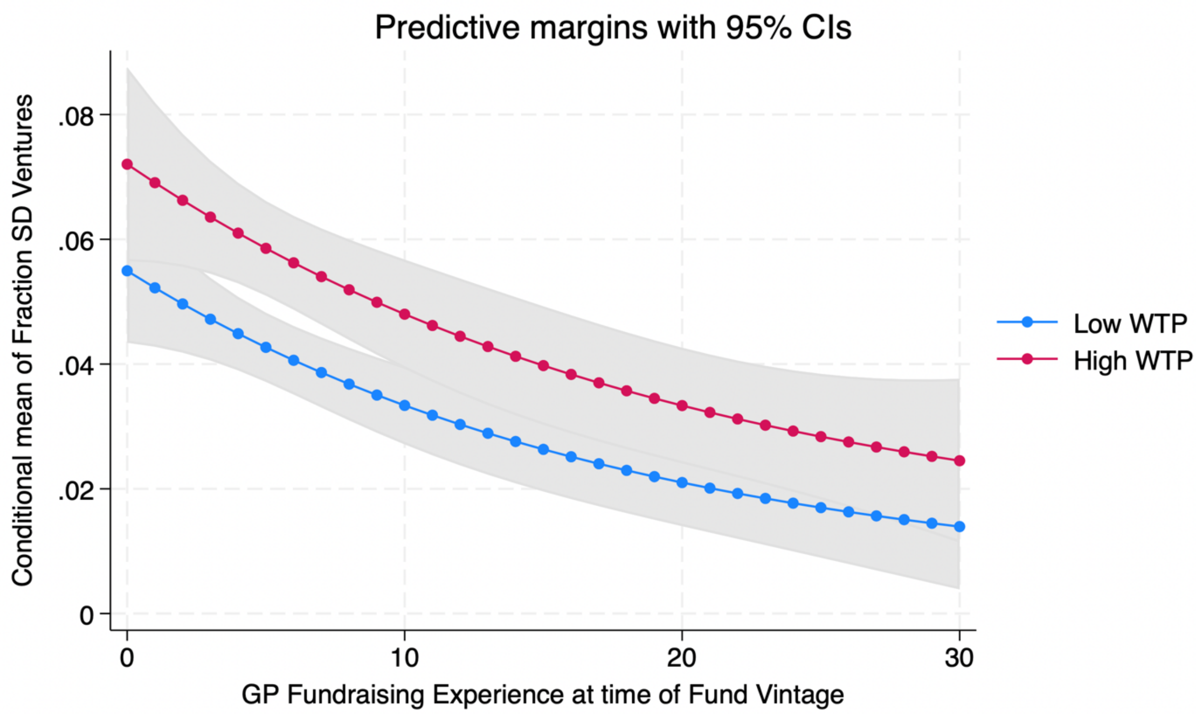

Figure 4.12 The Effect of High WTP LP on Fund Sustainability across GP Fundraising Experience (Sample of liquidated and fully invested funds)

Table 4.16 Alternative Measure of Impact Fund

Dependent Variable: Fund Sustainability Orientation (Fraction of SD ventures in portfolio)						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fund backed by High WTP LPs	0.12***	0.12***	0.12***	0.10***	0.10***	0.09***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Prefer Impact		0.36***	0.34***	0.33***	0.34***	0.31***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Fund Size		-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First Fund		0.16***	0.17***	0.19***	0.19***	0.14***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Comanaged Fund		-0.01	-0.01	-0.03	-0.02	-0.00
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Vintage (Trend)			0.02***			
			(0.00)			
GP Fundraising Experience						-0.03***
						(0.01)
GP Fundraising Experience - Squared						0.00**
						(0.00)
GP Had Experience in SD ventures						0.39***
						(0.04)
Early-Stage Fund		-0.06	-0.09**	-0.10***	-0.11***	-0.11***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Later-Stage Fund		0.07	0.05	0.02	0.01	0.05
		(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
Buyout Fund		0.01	0.02	0.01	-0.00	0.05
		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Constant	-1.63***	-1.66***	-1.92***	-2.19***	-2.02***	-1.92***
	(0.02)	(0.04)	(0.05)	(0.21)	(0.27)	(0.26)
Observations	4,419	4,277	4,277	4,277	4,277	4,277
Fund Region FE		YES	YES	YES	YES	YES
Vintage Year FE				YES	YES	YES
Vintage Year * Fund Region FE					YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.17 Alternative Measure of Independent Variable: Fraction of high WTP LPs in Fund

Dependent Variable: Fund Sustainability Orientation (Fraction of SD ventures in portfolio)						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fraction High-WTP LP	0.17***	0.10**	0.11***	0.09**	0.08*	0.08*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Impact Fund		0.87***	0.84***	0.80***	0.80***	0.70***
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Fund Size		-0.00*	-0.00**	-0.00**	-0.00***	-0.00**
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First Fund		0.12***	0.14***	0.16***	0.15***	0.12***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Comanaged Fund		0.01	0.01	-0.00	0.00	0.01
		(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Vintage (Trend)			0.02***			
			(0.00)			
GP Fundraising Experience						-0.03***
						(0.01)
GP Fundraising Experience - Squared						0.00**
						(0.00)
GP Had Experience in SD ventures						0.39***
						(0.04)
Early-Stage Fund		-0.06	-0.09**	-0.10***	-0.11***	-0.11***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Later-Stage Fund		0.07	0.05	0.02	0.01	0.05
		(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
Buyout Fund		0.01	0.02	0.01	-0.00	0.05
		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Constant	-1.65***	-1.57***	-1.82***	-2.05***	-1.81***	-1.75***
	(0.02)	(0.04)	(0.05)	(0.21)	(0.36)	(0.35)
Observations	4,419	4,277	4,277	4,277	4,277	4,277
Fund Region FE		YES	YES	YES	YES	YES
Vintage Year FE				YES	YES	YES
Vintage Year * Fund Region FE					YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.18 Additional Analyses

VARIABLES	(1) MA	(2) IPO	(3) Out-of-Business	(4) Env-Venture
Fund backed by High WTP LPs	0.01	-0.03	0.03*	0.08**
	(0.02)	(0.03)	(0.02)	(0.03)
Impact Fund	-0.13**	-0.35***	0.02	0.66***
	(0.05)	(0.08)	(0.06)	(0.07)
Fund Size	0.00**	0.00***	-0.00***	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
First Fund	0.01	-0.06	0.08***	0.11**
	(0.03)	(0.04)	(0.03)	(0.05)
Comanaged Fund	-0.15***	0.11*	0.07	-0.00
	(0.04)	(0.06)	(0.05)	(0.08)
GP Age	0.01**	0.01**	-0.00	-0.03***
	(0.00)	(0.00)	(0.00)	(0.01)
GP Age - Squared	-0.00	-0.00	-0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
GP Had Experience in SD ventures	-0.05***	0.05*	0.05**	0.37***
	(0.02)	(0.03)	(0.02)	(0.04)
Early-Stage Fund	0.06***	-0.25***	0.06**	-0.06
	(0.02)	(0.03)	(0.02)	(0.04)
Later-Stage Fund	0.11***	0.08**	-0.30***	0.07
	(0.03)	(0.04)	(0.04)	(0.05)
Buyout Fund	0.26***	-0.02	-0.24***	0.14**
	(0.04)	(0.05)	(0.05)	(0.06)
Constant	0.73***	-1.06***	-1.75***	-1.74***
	(0.14)	(0.37)	(0.39)	(0.35)
Observations	4,277	4,277	4,277	4,277
Fund Region FE	YES	YES	YES	YES
Vintage Year FE	YES	YES	YES	YES
Vintage Year * Fund Region FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.19 Instrumental Variable Specification (H1)

First-stage DV: Fund backed by High WTP LPs (dummy) Second-stage DV: Fund Sustainability Orientation (Fraction of SD ventures in portfolio)						
VARIABLES	(1) First-stage	(2) Second-stage	(3) First-stage	(4) Second-stage	(5) First-stage	(6) Second-stage
Fund backed by High WTP LPs		0.17**		0.19***		0.21**
		(0.07)		(0.07)		(0.08)
Share Low WTP LP (Instrument)	-1.13***		-1.14***		-1.14***	
	(0.03)		(0.03)		(0.03)	
Impact	0.11***	0.68***				
	(0.04)	(0.07)				
Prefer Impact			-0.02	0.31***		
			(0.02)	(0.04)		
Fund Size	0.00***	-0.00**	0.00**	-0.00***	0.00*	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First Fund	0.01	0.12***	0.01	0.14***	0.01	0.10*
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.05)
Comanaged Fund	0.05	0.05	0.05	0.01	0.05	-0.08
	(0.03)	(0.07)	(0.03)	(0.07)	(0.04)	(0.09)
GP Fundraising Experience	-0.00	-0.03***	-0.00	-0.03***	-0.00	-0.02**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
GP Fundraising Experience - Squared	0.00	0.00***	0.00	0.00**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GP Had Experience in SD ventures	0.01	0.37***	0.02	0.40***	0.03*	0.38***
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)
Early-Stage Fund	-0.08***	-0.06	-0.08***	-0.10***	-0.07***	-0.06
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)
Later-Stage Fund	0.09***	0.07	0.09***	0.06	0.10***	-0.01
	(0.02)	(0.05)	(0.02)	(0.05)	(0.03)	(0.06)
Buyout Fund	0.06**	0.13**	0.06**	0.05	0.11***	0.09
	(0.02)	(0.05)	(0.02)	(0.06)	(0.03)	(0.08)
Constant	1.08***	-1.82***	1.08***	-2.13***	1.13***	-5.01***
	(0.24)	(0.35)	(0.24)	(0.22)	(0.36)	(0.21)
Observations	4,277	4,277	4,277	4,277	3,294	3,294
Vintage Year FE	YES	YES	YES	YES	YES	YES
Fund Region FE	YES	YES	YES	YES	YES	YES
Vintage Year * Fund Region FE	YES	YES	YES	YES	YES	YES
F-statistic	742.74		757.57		542.24	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.20 Instrumental Variable Specification (H2)

First Stage: Model 1 & 4: Fraction High WTP LP First Stage: Model 2: Fraction High WTP LP × Impact First Stage: Model 5: Fraction High WTP LP × Fund Located in EU Second-stage: Model 3 & 6 DV: Share SD Ventures						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fraction High WTP LP			0.26***			0.30***
			(0.09)			(0.10)
Impact Fund	0.05	1.03***	1.00***			
	(0.04)	(0.04)	(0.20)			
Fraction High WTP LP × Impact Fund			-0.53*			
			(0.30)			
Fund Located in EU				0.03	0.98***	0.30***
				(0.03)	(0.02)	(0.08)
Fraction High WTP LP × Fund Located in EU						-0.26
						(0.20)
Availability of Low WTP LP	-0.94***	0.00		-0.89***	0.01***	
	(0.02)	(0.00)		(0.02)	(0.00)	
Availability of Low WTP LP × Impact	0.16*	-0.81***				
	(0.09)	(0.09)				
Availability of Low WTP LP × Fund Located in EU				-0.05	-0.96***	
				(0.04)	(0.03)	
Fund Size	0.00	-0.00	-0.00**	0.00	0.00*	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
First Fund	0.01	0.00	0.12***	0.01	-0.00	0.12***
	(0.02)	(0.00)	(0.04)	(0.02)	(0.01)	(0.04)
Comanaged-Fund	0.05**	-0.00	0.04	0.06**	0.06***	0.05
	(0.02)	(0.01)	(0.07)	(0.02)	(0.02)	(0.07)
GP Fundraising Experience	0.00	0.00	-0.03***	0.00	-0.00	-0.03***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
GP Fundraising Experience - Squared	0.00	-0.00	0.00***	0.00	0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GP Had Experience in SD ventures	0.01	-0.00	0.37***	0.01	0.00	0.38***
	(0.01)	(0.00)	(0.04)	(0.01)	(0.00)	(0.04)
Early-Stage Fund	-0.05***	-0.00	-0.06	-0.05***	-0.01*	-0.05
	(0.01)	(0.00)	(0.04)	(0.01)	(0.01)	(0.04)
Later-Stage Fund	0.05***	0.00	0.08	0.05***	-0.00	0.08
	(0.02)	(0.00)	(0.05)	(0.02)	(0.01)	(0.05)
Buyout Fund	0.05***	0.00*	0.14**	0.05***	0.01	0.14***
	(0.01)	(0.00)	(0.05)	(0.01)	(0.01)	(0.05)
Constant	0.98***	-0.00	-1.87***	0.92***	-0.00	-2.27***
	(0.02)	(0.00)	(0.33)	(0.04)	(0.01)	(0.21)
Observations	4,275	4,275	4,275	4,275	4,275	4,275
Vintage Year FE	YES	YES	YES	YES	YES	YES
Fund Region FE	YES	YES	YES	NO	NO	NO
Vintage Year * Fund Region FE	YES	YES	YES	NO	NO	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.21 Instrumental Variable Specification (H3)

First Stage: Model 1 & 4: Fraction High WTP LP First Stage: Model 2: Fraction High WTP LP × First Fund First Stage: Model 5: Fraction High WTP LP × GP Fundraising Experience Second-stage: Model 3 & 6 DV: Share SD Ventures						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Fraction High WTP LP			0.33***			0.28***
			(0.11)			(0.11)
First Fund	0.05*	0.96***	0.15*	0.00	0.16	0.10**
	(0.03)	(0.02)	(0.08)	(0.02)	(0.10)	(0.04)
Fraction High WTP LP × First Fund			-0.10			
			(0.17)			
GP Fundraising Experience	0.00	-0.02***	-0.03***	-0.00	0.89***	-0.03***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.05)	(0.01)
Fraction High WTP LP × GP Fundraising Experience						-0.00 (0.01)
Availability of Low WTP LP	-0.89***	-0.56***		-0.96***	-0.44**	
	(0.03)	(0.03)		(0.02)	(0.22)	
Availability of Low WTP LP × First Fund	-0.08* (0.04)	-0.96*** (0.03)				
Availability of Low WTP LP × GP Fundraising Experience				0.00 (0.00)	-0.80*** (0.06)	
Fund Size	0.00	-0.00	-0.00**	0.00	0.00**	-0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Comanaged-Fund	0.07***	-0.00	0.04	0.06**	0.45	0.05
	(0.03)	(0.00)	(0.07)	(0.02)	(0.30)	(0.07)
GP Fundraising Experience - Squared	-0.00 (0.00)	-0.00 (0.00)	0.00*** (0.00)	0.00 (0.00)	0.00 (0.00)	0.00*** (0.00)
GP Had Experience in SD ventures	0.01	0.01	0.37***	0.01	0.10	0.37***
	(0.01)	(0.01)	(0.04)	(0.01)	(0.10)	(0.04)
Early-Stage Fund	-0.05***	-0.01	-0.04	-0.05***	-0.36***	-0.05
	(0.01)	(0.01)	(0.04)	(0.01)	(0.11)	(0.04)
Later-Stage Fund	0.05***	0.01	0.07	0.05***	0.46***	0.07
	(0.02)	(0.01)	(0.05)	(0.02)	(0.16)	(0.05)
Buyout Fund	0.04***	0.01**	0.13**	0.04***	0.16	0.11**
	(0.01)	(0.01)	(0.06)	(0.01)	(0.13)	(0.06)
Constant	0.92***	0.01	-2.06***	0.99***	0.11	-1.88***
	(0.04)	(0.03)	(0.22)	(0.02)	(0.20)	(0.33)
Observations	4,128	4,128	4,128	4,128	4,128	4,128
Vintage Year FE	YES	YES	YES	YES	YES	YES
Fund Region FE	YES	YES	YES	YES	YES	YES
Vintage Year * Fund Region FE	NO	NO	NO	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 5 Conclusion

This dissertation is motivated by advancing understanding of the role played by venture capital for entrepreneurial startups. The first essay focuses on startups' technological positioning in a mature context, and directly analyzes the direction and focus of startups' technological activities after CVC investment. The second essay studies the role of VC in shaping industry emergence and startups' product positioning, and underscores the essential role played by VC in the entrepreneurial process. The third essay explores how the source of VC funding impacts the financing of sustainability-driven ventures. Together, these essays provide new insights into how venture capital contributes to shape entrepreneurial activities.

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