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Startup Accelerators, Information Asymmetry, and Corporate Venture Capital Investments

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Abstract. Beyond financial incentives, investments by Corporate Venture Capitalists (CVCs) are often motivated by strategic objectives, such as gaining early exposure to emerging technologies. However, in the presence of information asymmetry, CVCs tend to invest in startups with a high degree of business relatedness—startups that are less risky but lacking in knowledge novelty—which are not ideal for achieving their strategic objectives. With startup accelerators showing promise in mitigating the information asymmetry problem, we examine how a CVC's investment pattern in a region shifts following a startup accelerator's entry, with a particular interest in the degree of business relatedness between the CVC's parent corporation and its portfolio companies. Analyses reveal that CVCs increase investments in startups that are *dissimilar* to their parent's business following the entry of startup accelerators. We show that the two pathways through which accelerators reduce information asymmetry—quality signals, and mentorship and training—likely contribute to this change. In addition, the change is most pronounced for CVCs whose parent firm operates in an *IT-using*—rather than an *IT-producing*—industry, suggesting that accelerators help *IT-using* firms gain a foothold in the technology space through CVC investments. These findings deepen the understanding of the role that startup accelerators play in the entrepreneurial ecosystem against the backdrop of digital transformation occurring in nearly every industry.

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Keywords: startup accelerator • information asymmetry • corporate venture capital • assessment and valuation problem

1. Introduction

Since its inception in the mid-1960s,[1] corporate venture capital has steadily grown into a significant player in the venture capital ecosystem. According to *Forbes*, corporate venture capitalists (CVCs) have participated in nearly a third of all recent U.S. venture deals, and 75 of the Fortune 100 companies are active in corporate venturing.[2] Compared with an independent venture capital firm that focuses solely on its fund's financial return, CVCs typically base their investment decisions on a combination of financial and strategic objectives (Ernst et al. 2005, Maula 2007). For example, the literature has emphasized a CVC's role in meeting its parent company's need for gaining exposure to emerging technologies (MacMillan et al. 2008, Benson and Ziedonis 2009) or complementing internal research and development (R&D) (Lerner 2013, Kim et al. 2016).

CVC investments offer a way for firms to ride the wave of digital transformation that has swept across every industry segment in recent years (Friedlmaier et al. 2018, Vial 2019). Emerging information technologies (IT) not only bring about new digital opportunities, but also disrupt mature industries and unseat well-established players. Novel digital applications that employ cutting-edge learning algorithms further enable new methods of dividing work and reshaping organizational boundaries, often to the detriment of incumbents (Westerman et al. 2014). Hence, it is in a firm's interest to strategically utilize CVC investments to benefit from the disruptive power of IT, rather than fall victim to it. As an example, Eastman Chemical Company was among the earliest corporate investors of *WebMethod Inc.*—a leading startup provider of business-to-business (B2B) e-commerce integration software.[3] Eastman subsequently leveraged WebMethod's technology to build a virtual B2B network with its trading partners in the late 1990s, enabling the secure exchange of highly specific and time-sensitive information associated with chemical products (Andal-Ancion et al. 2003).

For Eastman to successfully navigate its digital transformation, it needed to not only invest in startups in the chemical industry, but also in industries outside its area of expertise, such as in the computer network or the software industry. More generally, to fulfill the strategic objectives of their parent corporation, CVCs need to invest in a diverse startup space (Dushnitsky and Lenox 2005b, Yang et al. 2014), including portfolio companies that are not closely related to their parent and therefore possess enough novel knowledge (Mowery et al. 1998; Keil et al. 2008a, b)—knowledge that originates "from breaking with the familiar trajectory and convention" (Arts and Fleming 2018, p. 1076). However, Eastman turned out to be the exception, rather than the rule; at the time, most CVCs were reluctant to venture into unfamiliar spaces, taking a conservative investment approach that avoided significant risk-taking but fell short of their strategic mission (Souitaris and Zerbinati 2014). The presence of information asymmetry, particularly, remains a major challenge that prevents CVCs from investing in a diversified portfolio that is optimized for their strategic objectives (Amit et al. 1998).

Startup accelerators (also called seed accelerators) are a recent development in the entrepreneurial space that promises to overcome some difficulties facing venture investors. A startup accelerator is a fixed-duration, cohort-based boot camp for early stage startups. It combines seed funding, mentorship, a shared workspace, and an audience of investors to speed up a startup's growth trajectory (Cohen and Hochberg 2014). Accelerators emerged in 2005 when *Y Combinator* launched a platform to nurture early stage ideas, and the model quickly gained global popularity. Some of the prominent accelerated startups include *Airbnb*, *DigitalOcean*, *Dropbox*, *Stripe*, and *Twitch*. Accelerators differ from traditional incubators in several aspects: their participation is competitive and cyclic; their business model often involves taking a small stake in the startups rather than charging rental or service fees; and they serve as an intermediary between venture investors and startups. This final aspect is exemplified by the "demo day" event at the conclusion of a cohort, where the participating entrepreneurs pitch their ideas to potential investors (Cohen 2013).

Many believe that startup accelerators will help reduce the degree of information asymmetry in the venture market in two ways (Venâncio and Jorge 2022, Charoontham and Amornpetchkul 2023). First, accelerators provide a signal of quality for the participating startups, due to a rigorous selection procedure before their admission. With the endorsement and legitimacy that startup accelerators lend to participating startups (Pauwels et al. 2016), investors may become more willing to invest in participating startups that are traditionally deemed too risky. Second, because of the intense feedback and mentorship they receive from accelerators, startups can more effectively develop, articulate, and position their innovative ideas. As a result, accelerators help investors understand and assess the value of startup ideas by quickly resolving confusion or uncertainty about the startup's core offering (Yu 2020).

Extant literature has offered some insights into startup accelerators, such as their impact on the regional entrepreneurial environment (Fehder and Hochberg 2014, Hochberg 2016), the extent to which they help the startups being accelerated (Hallen et al. 2019), and their competition and convergence with crowdfunding (Winston Smith et al. 2013). Yet, it remains unclear whether accelerators play a significant role in reshaping CVCs' investment behavior through the services they provide and what the implications are for CVCs' strategic objectives. We aim to bridge the gap by investigating the influence of accelerators' entry on CVCs through the theoretical lens of information asymmetry, with a specific interest in their portfolio firms' relatedness to the business of their parent organization, a critical strategic consideration. To discover the pattern changes, we compile a unique panel data set combining multiple data sources, including investments made by CVCs that were actively investing in the United States between 1996 and 2016; the introduction of accelerators in various metropolitan areas; and CVC parent firms' fundamentals. Using text mining techniques, we develop robust measures of business relatedness between a CVC and its portfolio firms and then classify its investments into those made in *similar* and *dissimilar* startups.

Our analyses reveal that CVCs, particularly those with a parent corporation that belongs to an *IT-using* industry (hereinafter called *IT-using CVCs*), significantly increase their investment in startups that are *dissimilar* to the CVC's parent firm following the entry of a startup accelerator. This finding supports our conjecture that accelerators alleviate the assessment and valuation problem and allow *IT-using* CVCs to become more comfortable investing in ventures they would otherwise avoid. In contrast, such pattern shifts are not evident for CVCs with parent companies that belong to an *IT-producing* industry (hereinafter called *IT-producing CVCs*). In addition, we conduct several mechanisms tests, which reveal that the two pathways through which accelerators may reduce information asymmetry—quality signals, and mentorship and training—both contribute to the changes in CVC investment patterns.

These results, combined with the fact that accelerated startups are predominantly in the IT sector (Crișan et al. 2021), suggest that *IT-using* CVCs venture into the digital technology space to a greater extent after the entry of startup accelerators, which have important implications for their parent companies' digital transformation. Particularly, we highlight that accelerators open up a channel through which technological progress in the *IT-producing* sector spills over into the *IT-using* industries (Liao et al. 2016), progress that, in turn, drives broad-based economic growth (Jovanovic and Rousseau 2005, Bloom et al. 2012). Interestingly, we find that these

CVCs do not simply substitute investments in similar startups with dissimilar ones, but instead commit more capital to dissimilar startups where accelerators enter. However, our results also show that *IT-producing* CVCs receive little benefit from the entry of accelerators, likely because of their familiarity with the high-tech domain and their already strong competence in assessing the quality of these startups. Our findings are robust across several modern difference-in-differences estimators that account for staggered treatment, in addition to the traditional two-way fixed effects estimator. We also find consistent results using three distinct measures of business relatedness: two derived from text mining techniques—vector embedding and topic modeling—and one using manually tagged industry classification of startups.

By studying the investment patterns of CVCs before and after the start of an accelerator in a region, our work reveals an emerging capital market intermediary that CVCs use to better serve their strategic objectives (MacMillan et al. 2008). Our findings suggest that accelerators help address the assessment and valuation problem for CVCs, thereby contributing to the extant startup accelerator literature, which has predominantly focused on their impact on accelerated startups and regional ecosystems (Hallen et al. 2019, Yu 2020). More broadly, we also contribute to literature on institutional forms and policies that help address informational challenges and nurture regional entrepreneurial activities (Fehder and Hochberg 2014). Finally, our research demonstrates the usefulness of text mining techniques in deriving a new measure of business relatedness between investor-investee pairs. In the process, we contribute to the technology entrepreneurship literature, as business relatedness has been challenging to measure in the absence of industry classification codes for startups (Haleblian and Finkelstein 1999, Keil et al. 2008b).

2. Related Literature and Research Questions

2.1. CVC Investments

A corporate venture capital fund serves as an equity investment arm of a well-established corporation, emulating investments in startups made by traditional venture capital firms (Gompers and Lerner 2000, Dushnitsky and Lenox 2006). Ideally, a functional CVC is established as an independent entity with a committed fund from a corporation to make capital investments and provide nonpecuniary resources and capabilities to the ventures that it invests in (Teece 1986, Siegel et al. 1988, Park and Steensma 2012, Alvarez-Garrido and Dushnitsky 2016).

CVCs differ from Independent Venture Capital (IVC) funds in several ways. First, unlike IVCs, which only seek financial returns, CVCs also look for strategic gains through their investments. Some of these strategic gains include complementing their parent firms' internal innovation efforts (Dushnitsky and Lenox 2005a, Ernst et al. 2005, Kim et al. 2016), acquiring market knowledge (Schildt et al. 2005), gaining early exposure to emerging technological innovation (Benson and Ziedonis 2009), and building options (Tong and Li 2011, Ceccagnoli et al. 2018). Second, unlike traditional venture capitalists (VCs), who raise capital from the market, CVCs receive their capital from their parent firms (Chemmanur et al. 2014). Finally, the personnel compensation structure in CVCs differs significantly from that in IVCs (Dushnitsky and Shapira 2010): CVCs typically adopt a more conservative approach to incentives, bonuses, and overall compensation (MacMillan et al. 2008). These structural differences affect how CVCs make entry and exit decisions (De Clercq et al. 2006).

With disruptive technologies precipitating the digital revolution, some researchers argue that incumbent firms leverage CVC investments to strengthen their dynamic capabilities and accelerate their digital transformation (Rossi et al. 2020, Horneber 2022). Many recognize that investing in digital technology startups is an important source of strategy renewal and new business opportunities, particularly for firms pursuing an ecosystem approach to innovation (Bagno et al. 2020). The IT industry has been a favored sector of interest to venture capitalists, accounting for over 60% of venture capital disbursements in recent years, with software, network and telecommunication, and information services as the typical hot spots (Gompers and Lerner 2001, OECD 2017). VC investments in IT startups surpass the sum of those made in all other "deep tech" industries, such as advanced materials, biotechnology, and photonics.[4] Several factors contribute to the strong interest in IT startups, such as a relatively short investment cycle, substantial financial payoffs, and many well-known successful cases (Kim et al. 2016).

2.2. Startup Accelerators

A startup accelerator follows a model in which early stage technology startups apply to join a cohort by pitching business ideas, some of which are admitted after a screening procedure. A startup accelerator combines mentorship, seed investment, and strategic networking under a single program. Most importantly, by aggregating startups into a cohort, it provides a common platform for external investors to evaluate these startups, reducing search costs for both entrepreneurs and investors (Hochberg 2016). The accelerator model has spread across the globe since its inception in 2005, with over 100 active accelerators in the United States alone. Together, they have accelerated over 8,000 startups, which have collectively raised over $100 billion as of this writing.[5]

Three themes of research have emerged from extant literature. The first research stream focuses on the impact of startup accelerators on the regional economic activities (Cohen and Hochberg 2014, Fehder and Hochberg 2014). For instance, research has shown that an accelerator entry into a region is associated with an increase in the volume of VC deals in the region (Fehder and Hochberg 2014).

The second stream focuses on the benefits of accelerator participation for startups. In general, startups backed by accelerators experience both a shortened timeline to success, measured by acquisition or initial public offering, and a shortened timeline to failure, allowing founders to pivot to new ideas more quickly (Winston Smith et al. 2013, Hallen et al. 2019, Yu 2020). Gonzalez-Uribe and Leatherbee (2018) note that the improved performance of startups can be attributed to the mentorship provided by accelerators, rather than to basic services, such as funding and coworking spaces. Studies also show that accelerators' organizational design has implications for mitigating bounded rationality in new ventures (Cohen et al. 2019).

The third stream examines the process through which entrepreneurs are screened and admitted to a startup accelerator. For instance, Winston Smith et al. (2013) investigate two popular accelerators—*Y Combinator* and *TechStars*—and show that accelerated startups exhibit greater founder mobility compared with those not backed by accelerators. They also find that accelerators prefer entrepreneurs who studied at a more prestigious university. These findings hint at systematic differences between entrepreneurs who participate in accelerator programs and those who do not, which may cast doubt on the benefits associated with accelerators because of potential selection and endogeneity issues.

2.3. Research Questions

Several gaps emerge from our literature review. First, the literature on CVC investment reveals that VCs have developed a set of tools and processes to address information asymmetry in deal screening, including due diligence policies, valuation methods, benchmark rates of return, and adjustments for risk (Wright and Robbie 1996). However, it is unclear whether VCs also rely on financial market intermediaries to alleviate their assessment and valuation problems. In the public equity market, a range of information intermediaries—including financial analysts and rating agencies—engage in private information collection and production, and it is well-known that investors benefit from the resulting reduction of information asymmetry (Healy and Palepu 2001). In contrast, little research has been done to show if information intermediaries in the VC market play a similar role, likely because of the historical lack of credible intermediaries. The advent of startup accelerators presents a rare example to explore this question.

A related gap in the literature is the insufficient understanding of how corporate VCs may respond to reduced information asymmetry and how these responses may influence their strategic missions. An expected outcome of reduced information asymmetry is that CVCs may increase the amount of their capital investments, which was the case for independent VCs following the entry of a startup accelerator (Fehder and Hochberg 2014). Whereas IVCs are motivated primarily by financial returns, CVCs have strong strategic incentives for their investments (Chesbrough 2002). Therefore, although earlier research has highlighted the potential benefits of information intermediaries to venture investors from a *financial* standpoint, it has offered limited evidence regarding their influence on the *strategic* aspects of VC investments, which is arguably a more important consideration in CVC investments.

We address these gaps by investigating how startup accelerators influence a CVC's investment patterns, with a focus on the strategic dimensions related to its investments. We are particularly interested in the degree of business relatedness between a CVC's parent and the set of portfolio firms the CVC invests in. Prior research on organizational learning suggests that the strategic objective of exposure to emerging technological innovations through CVC investments is better served by investing in moderately distant startups, rather than closely related ones, because the novelty of learning decreases with greater knowledge overlap (Keil et al. 2008b, Sapienza et al. 2004). Additionally, disruptive technologies often emerge from other fields that sometimes lead to unforeseen, but important, implications for the focal market (Pan et al. 2019). Yet, evaluating startup ideas from a less related domain requires specialized expertise that CVCs often find challenging to develop, making the service of startup accelerators potentially valuable. Thus, we seek to answer the question: *Does the entry of a startup accelerator lead to an increase in a CVC's investment in startups that are less similar to its parent firm?*

A secondary objective of our study is to explore the heterogeneities in CVCs' investment strategy changes in response to an accelerator's entry, particularly within the context of the ongoing wave of digital transformation and productivity gains in *IT-using* industries (Bloom et al. 2012). We conjecture that startup accelerator programs are particularly beneficial to incumbents in *IT-using* industries who are undergoing digital transformation, given that a majority of these accelerated startups are related to information and communication technologies to some degree (Crișan et al. 2021). Compared with CVCs with an *IT-producing* parent company, which likely already possess specialized expertise in the high-tech space, *IT-using* CVCs face greater difficulties in evaluating technology startups and, therefore, stand to benefit from the services that accelerators provide to a greater extent. Therefore, the second research question we ask is: *Do IT-using CVCs benefit more from the reduction in information asymmetry associated with an accelerator's entry than IT-producing CVCs, leading them to increase investment in dissimilar startups to a greater extent?*

3. Data and Methods

3.1. Data Sources and Sample

We compiled the data set for our empirical investigation from multiple sources. We gathered information on CVC investments from Thomson Reuters VentureXpert and firm-level CVC parent characteristics from Compustat. Data on accelerators, including their names, the time and location of their cohorts, and the set of startups they accelerated in each cohort, were sourced from Seed-DB. To measure the degree of business relatedness between CVCs and the portfolio firms they invested in, we retrieved the business descriptions of CVC parent firms from SEC-Edgar and the business descriptions of startups from VentureXpert, augmented with the business descriptions from Crunchbase. The rest of this subsection provides details of the data collection process.

Thomson Reuters VentureXpert, a database that keeps track of venture capital investments, has been widely used in extant information systems (IS) entrepreneurship studies (Aggarwal et al. 2012, Singh et al. 2015, Kim et al. 2016, Subramanian et al. 2021). We collected records of all investment activities by CVCs in the United States between 1996 and 2016. We restricted the sample to investments made by CVC funds that remained active after 2005, as it marks the inception of the first startup accelerator, Y Combinator. We define CVC investments following the classification scheme outlined in Dushnitsky and Lenox (2005b). In total, 11,915 investments made in 6,302 startups during this period were classified as CVC investments.[6]

We utilized the SEC-Edgar database to collect annual 10K reports of public CVC parent firms, from which we extracted business descriptions.[7] We used the VentureXpert database to obtain business descriptions of startups. Wherever available, we augmented the VentureXpert business descriptions with mini business descriptions retrieved from Crunchbase, a popular website that keeps track of startups and their financing deals (Shi et al. 2016). We then used these business descriptions as input for text analysis (as described in Section 3.2), which allowed us to calculate the business relatedness between a CVC and its portfolio firms.[8] Part I of Online Appendix D provides sample snapshots of business descriptions from VentureXpert, Crunchbase, and SEC-Edgar, as well as an illustration of how these descriptions evolved in 10K reports of these firms over the years.[9]

The Seed-DB database tracks information on startup accelerators by aggregating data from popular sources such as Crunchbase and AngelList. The website provides details on startups that participated in startup-accelerator cohorts and has been used in extant research examining accelerators (e.g., Hochberg 2016, Cohen et al. 2019, Johnson et al. 2022). We used this database to obtain cohort-level data, as well as the year when a region experienced its first accelerator.

Our primary sample results from combining the VentureXpert CVC investment data with the Compustat fundamentals data on the parent firms of CVCs. Particularly, we identified parent firms based on the CVC funds' names and descriptions, manually linking each CVC fund to its respective parent company. This process resulted in the identification of 632 CVC funds owned by 389 parent public firms. These public CVC firms made investments in 141 Metropolitan Statistical Areas (MSAs), 52 of which experienced an accelerator entry during the 1996–2016 sample period.

3.2. Variables

Tables 1 and 2 describe the main variables and provide descriptive statistics, respectively. Online Appendix Table A1 provides correlations between variables in the matched sample. Because ours is a balanced panel data set aggregated to the CVC-MSA-year level, rather than at the investment level, summary statistics are calculated based on CVC-MSA-year observations. The details on investment-level data are provided in Online Appendix Table A2.

3.2.1. Dependent Variables. The primary measure of business relatedness between a CVC and a startup is constructed using text mining, which is then used to classify a CVC's investments into *similar* and *dissimilar* ones. Extant research often uses industry classification codes, such as the *North American Industry Classification System* (NAICS), *Standard Industrial Classification*, or *Global Industry Classification Standard*, to measure the business relatedness of two firms (Bhojraj et al. 2003, Keil et al. 2008b, Kile and Phillips 2009). We cannot follow the conventional approach because such industry classification codes are not readily available for the privately held startups. Therefore, we employed a combination of the vector embedding technique (e.g., Mikolov et al. 2013) and cosine similarity method to gauge the similarities between the business of a CVC parent and a portfolio company it invests in (Hoberg and Phillips 2016, Pan et al. 2019). These vector embedding techniques overcome some limitations inherent in traditional methods like term frequency-inverse document frequency (Hinneburg and Keim 1999).

3.2.1.1. Business Relatedness. We calculated a business-relatedness score for each startup-CVC investor pair, as illustrated in Figure 1. The cosine similarity value is bounded between zero and one. Intuitively, the cosine similarity is close to 1 when the business

Table 1. Variable Description

Variable	Definition
Dependent variables	
$similar\_amount_{ijt}$	Total amount (in millions of USD) of investments made in startups that are similar to CVC firm *i* in MSA *j* and year *t*. Similar investment is bifurcated based on the median business relatedness between startups and their investor CVCs.
$dissimilar\_amount_{ijt}$	Total amount (in millions of USD) of investments made in startups that are not similar to CVC firm *i* in MSA *j* and year *t*. Dissimilar investment is bifurcated based on the median business relatedness between startups and their investor CVCs.
Difference-in-Differences (DiD) variables	
$treated_{ij}$	A dummy that takes a value of 1 if a CVC *i* receives the treatment (accelerator entry) in MSA *j* in any year.
$post\_entry_{jt}$	A dummy that takes a value of 1 if MSA *j* has experienced an accelerator entry in year *t* or earlier.
Explanatory and control variables	
$R\&D\_investment_{it}$	R&D investment of CVC firm *i* in year *t* (in millions of USD)
$coordination\_investment_{it}$	Coordination investments of CVC firm *i* in year *t* (in millions of USD), computed as [SG&A expenses – R&D expenses], following prior work (e.g., Ray et al. 2009, Im et al. 2013)
$revenue_{it}$	Total revenue of CVC firm *i* in year *t* (in millions of USD)
$coinvestors_{ijt}$	The average number of coinvestors other than itself across all deals where CVC *i* invested in MSA *j* and year *t*
$total\_funding\_round_{jt}$	Count of funding rounds received by all startups in an MSA *j* and year *t*.
$IT\_producing\_CVC_i$	A dummy that carries the value of one for CVCs whose parent firm is classified as an IT-producing firm following prior research (e.g., Kim et al. 2016, Pan et al. 2019)
$IT\_Intensity_i$	IT intensity of a firm at the four-digit NAICS industry level, computed using the CII database following prior research (e.g., Huang et al. 2022).

description of the startup is nearly identical to that of the CVC's parent firm and has a value of 0 when the business descriptions are completely unrelated. We multiplied the raw similarity score by 100 to represent the business relatedness as a percentage.

3.2.1.2. *Investment Amounts in Similar and Dissimilar Startups.* The median business relatedness of startup-CVC pairs is 56.25 (on a scale of 0–100). An investment, where the business relatedness of the startup-CVC pair is greater than 56.25, is classified as an investment in a *similar* startup.[10] The variable $similar\_amount_{ijt}$ is the total investment made by CVC *i* in similar startups in MSA *j* and year *t*. Conversely, a CVC investment where the business relatedness is less than 56.25 is classified as an investment in a *dissimilar* startup. The variable $dissimilar\_amount_{ijt}$ is the total investment made by CVC *i* in dissimilar startups in MSA *j* and year *t*. Part II of Online Appendix D provides a detailed example of this process, focusing on investments that a CVC made in two startups—a similar one and a dissimilar one. In Section 5.2.3.2, we further test the robustness of this classification by using two independent measures of business relatedness: a similarity score based on manually tagged NAICS codes of startups and a topic modeling-based measure.

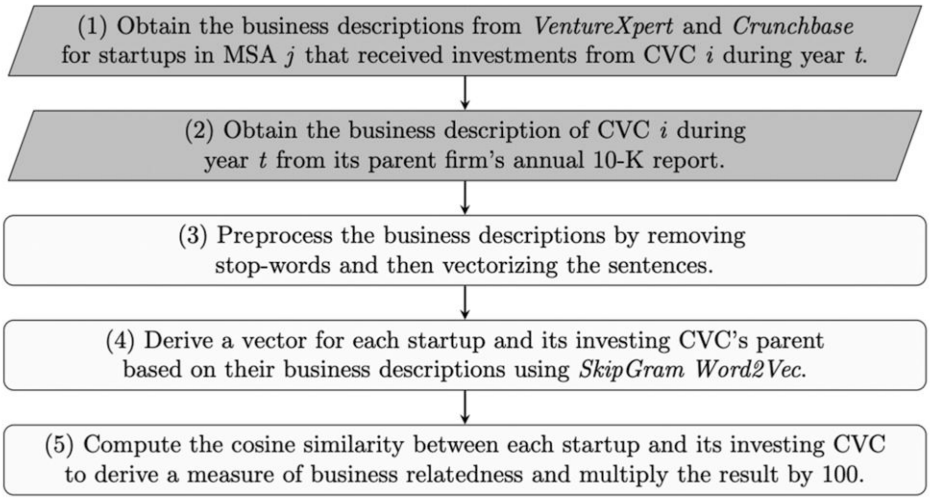
3.2.2. Explanatory Variables. Because we use a *Difference-in-Differences* approach, where the entry of an accelerator is considered the treatment (with more details presented in Section 3.3), the primary explanatory variables are *treated* and *post_entry*. In addition, we

Table 2. Summary Statistics

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
$similar\_amount_{ijt}$	Million USD	49,854	1.209	17.659	0	2,566.7
$dissimilar\_amount_{ijt}$	Million USD	49,854	1.131	9.166	0	607.9
$treated_{ij}$	Binary	49,854	0.5	0.5	0	1
$post\_entry_{jt}$	Binary	49,854	0.35	0.473	0	1
$R\&D\_investment_{it}$	Million USD	49,854	1,086.0	2,138.3	0	16,085
$coordination\_investment_{it}$	Million USD	49,854	3,096.7	6,120.6	0	45,408
$revenue_{it}$	Million USD	49,854	22,701.6	39,600.4	0	433,526
$coinvestors_{ijt}$	Coinvestors per deal	49,854	0.045	0.274	0	7
$total\_funding\_round_{jt}$	Count of investments	49,854	26.269	42.183	0	385
$IT\_producing\_CVC_i$	Binary	49,854	0.436	0.496	0	1
$IT\_intensity_i$	Continuous within (0,1)	49,854	0.061	0.061	0.001	0.825

Note. Obs, observations; Std. Dev., standard deviation.

Figure 1. Calculating Business Relatedness Score for Startup-CVC Pair



evaluated the investment pattern changes of CVCs by *IT-producing* and *IT-using* parent firms separately across all models.

$treated_{ij}$: This dummy variable takes a value of one if CVC i witnesses the entry of an accelerator in MSA j during any year of our sample period.

$post\_entry_{jt}$: This dummy variable takes a value of one if MSA j experienced an accelerator entry in year t or any previous year.

$IT\_producing\_CVC_i$: We divided CVCs into two categories—CVCs with an *IT-producing* parent firm (i.e., *IT-producing* CVCs) and CVCs with an *IT-using* parent firm (i.e., *IT-using* CVCs). We followed prior literature (e.g., Kim et al. 2016, Pan et al. 2019) and used 24 four-digit NAICS codes to identify *IT-producing* CVCs. A CVC whose parent firm fell outside these 24 NAICS codes was deemed an *IT-using* CVC. Online Appendix Table B1 provides the detailed process for identifying *IT-producing* CVCs.

3.2.3. Control Variables. We collected R&D investment data of CVCs' parent firms from Compustat and accounted for their R&D spending, as it represents the overall spending of a firm on innovation efforts. Because gaining a window on emerging technologies is a major motivation for CVC investment (Benson and Ziedonis 2009), there may be a correlation between R&D spending levels and CVC investments. We controlled for the firm's coordination investment[11] (Ray et al. 2009, Im et al. 2013). The CVC parent firm's revenue was included as a proxy for firm size to address the concern that the scale of CVC investments could be driven by the company size. Missing values in R&D investments and coordination investments were addressed by using imputation methods similar to those in prior work.[12] We included the count of investment deals made by all VCs in MSA j and year t, a proxy for overall entrepreneurial activities in the region, in all regressions. We also included the average number of coinvestors (other than itself) per deal for CVC i in MSA j and year t.[13]

3.3. Methods

To answer the research question regarding the impact of an accelerator's entry on a CVC investor's investment strategy, we adopted a Difference-in-Differences (*DiD*) model. The *DiD* estimation technique has been commonly used to study the causal impact of *treatment* on the *treated* observations (Meyer 1995). In our setting, the starting of the operation of the first accelerator in MSA j is considered the treatment, and the year of its entry t marks the beginning of the *post_entry* period for region j. A total of 52 MSAs in our sample witnessed the entry of an accelerator during the study period (1996–2016). Thus, the *treated* group consists of CVC-MSA pairs that experienced an accelerator's entry, and we retain only those CVC-MSA pairs where the CVC made at least one investment in the MSA during any year of the study period.[14] The entries of accelerators were staggered—that is, different MSAs experienced their first accelerator entry in different years. We address the staggered entry by following two distinct procedures recommended in the literature. The first approach involves normalizing the treatment time within a two-way fixed effects (TWFE) estimator (Gao and Zhang 2017, Mayya and Viswanathan 2024). The year of treatment is marked as $t = 0$, with the pretreatment and posttreatment periods sequenced in reverse chronological $(\ldots\ -2,\ -1)$ and chronological order $(1, 2, \ldots)$, respectively. The second approach involves employing modern estimators, such as those developed by Callaway and Sant'Anna (2021) or Borusyak et al. (2024), which explicitly account for biases that the TWFE estimator may introduce under the staggered treatment scenario.

3.3.1. Determining the Control Group. A key challenge in obtaining insights using *DiD* in a nonexperimental setting is that the assignment of treatment is not random. When treatment assignment cannot be controlled, the literature recommends using matching (Dehejia and Wahba 2002), where the data should be preprocessed to ensure that the treated and control groups are equally likely to be treated (Abadie 2005). In our context, MSAs that see accelerators starting their operations may be fundamentally different from MSAs that do not. Hence, our matching algorithm used the "not-yet-treated" observations as the control group, a commonly employed method in policy adoption and evaluation literature (e.g., Hoynes et al. 2016, Jung et al. 2019). This approach accounts for unobservable CVC-MSA characteristics that could influence the likelihood of treatment. Specifically, we matched a CVC-MSA that sees an accelerator entry in year t (the *treated* unit) with a "not-yet-treated" CVC-MSA, one that will eventually see an accelerator entry in years $t+1$ or beyond. For matching, we utilized a set of CVC-specific pretreatment characteristics, including the total investment amount by the CVC in the MSA, the *similar* and *dissimilar* investment amounts, and the business-relatedness score, as well as other time-varying covariates from Compustat, such as the CVC's revenue, R&D investment, and coordination investments. Given the time-varying nature of the covariates, we used all pretreatment periods following the suggestions of Chabé-Ferret (2017) and computed the propensity score using an approach similar to Mayya and Li (2025). Specifically, we applied one-to-one nearest neighbor matching *without* replacement to ensure that each control CVC-MSA pair was matched only once with a treated CVC-MSA. Online Appendix Table C1 indicates that the covariates are well-balanced after matching. The matching procedure resulted in a sample of 1,187 treated and 1,187 control CVC-MSA pairs, with 49,854 CVC-MSA-year observations over 21 years. It is important to note that for any observation in the control group, $treated_{ij}$ is set to zero, despite the CVC-MSA getting eventually treated.

3.3.2. Main Analysis. To examine the relationship between the commencement of an accelerator's activities in a region and CVCs' investment strategies, we treat the *similar* and *dissimilar investment amounts* by the CVCs as dependent variables in separate equations. We used the log value of the dependent variables to address the skewness of their distributions (and added one to these variables prior to applying the log transformation). Specifically, the equations for the *DiD* models are as follows:

$$log(similar\_investment_{ijt}) = \beta_0^s + \beta_1^s * post\_entry_{jt} + \beta_2^s * treated_{ij} * post\_entry_{jt} + \boldsymbol{\beta_3^s} * \boldsymbol{x_{ijt}} + \gamma_{ij}^s + \eta_t^s + \varepsilon_{ijt}^s, \quad (1(a))$$

$$log(dissimilar\_investment_{ijt}) = \beta_0^d + \beta_1^d * post\_entry_{jt} + \beta_2^d * treated_{ij} * post\_entry_{jt} + \boldsymbol{\beta_3^d} * \boldsymbol{x_{ijt}} + \gamma_{ij}^d + \eta_t^d + \varepsilon_{ijt}^d, \quad (1(b))$$

where $\boldsymbol{x_{ijt}}$ represents a vector of control variables, and superscripts s and d denote the coefficients for the similar and dissimilar models, respectively. If startup accelerators help mitigate information asymmetry, they should cause a CVC firm to invest in startups that are dissimilar to its core business. Hence, we expect the coefficient of β_2^d to be positive and significant. As a robustness check, we also estimated the two equations simultaneously using a Seemingly Unrelated Regression (SUR) specification, which improves estimation efficiency by allowing the disturbances of the two equations to be correlated.[15] The models incorporate two fixed effects: one for the MSA-CVC combination (γ_{ij}) and one for the year (η_t). Using the fixed-effect γ_{ij} accounts for firm-region-invariant heterogeneities in the MSA-CVC pair (e.g., the incentive structure of a CVC), ensuring that the analysis focuses on within-firm-region variations in the dependent variables.

Another key objective of this research is to study whether *IT-producing* CVCs and *IT-using* CVCs adopt different investment strategies in response to accelerator entries. To contrast the investment strategies of *IT-producing* and *IT-using* CVCs, we employed a triple-difference framework (Olden and Møen 2022) by incorporating a three-way interaction term involving *DiD* terms and the *IT-producing_CVC* dummy:

$$log\,(similar\_investment_{ijt}) = \beta_0^s + \beta_1^s * post\_entry_{jt} + \beta_2^s * treated_{ij} * post\_entry_{jt} + \beta_3^s * treated_{ij} * post\_entry_{jt} * IT\_producing\_CVC_i + \boldsymbol{\beta_4^s} * \boldsymbol{x_{ijt}} + \gamma_{ij}^s + \eta_t^s + \varepsilon_{ijt}^s, \quad (2(a))$$

$$log(dissimilar\_investment_{ijt}) = \beta_0^d + \beta_1^d * post\_entry_{jt} + \beta_2^d * treated_{ij} * post\_entry_{jt} + \beta_3^d * treated_{ij} * post\_entry_{jt} * IT\_producing\_CVC_i + \boldsymbol{\beta_4^d} * \boldsymbol{x_{ijt}} + \gamma_{ij}^d + \eta_t^d + \varepsilon_{ijt}^d, \quad (2(b))$$

This triple-difference specification contrasts the trajectory of *IT-producing* CVCs, which we expect to be affected to a lesser extent by the treatment, with the trajectory of *IT-using CVCs*. It suffices to establish parallel trends in the *DiD* model as an essential assumption for parallel trends in triple-difference models (Olden and Møen 2022).

3.3.3. Parallel Trends. We followed prior research (e.g., Autor 2003) to conduct an event study and test whether CVC investments before the treatment (i.e., before the first accelerator begins operations in the MSA) are similar and parallel, an important assumption for the *DiD* framework. Specifically, the equations to test the parallel trends are:

$$log(similar\_investment_{ijt}) = \beta_0^s + \sum_{k=-8}^{6} \tau_{t+k}^s * relative\_time_{jt+k} + \boldsymbol{\beta_1^s} * \boldsymbol{x_{ijt}} + \gamma_{ij}^s + \eta_t^s + \varepsilon_{ijt}^s,$$

$$log(dissimilar\_investment_{ijt}) = \beta_0^d + \sum_{k=-8}^{6} \tau_{t+k}^d * relative\_time_{jt+k} + \boldsymbol{\beta_2^d} * \boldsymbol{x_{ijt}} + \gamma_{ij}^d + \eta_t^d + \varepsilon_{ijt}^d,$$

where $relative\_time_{jt+k}$ is set to one if MSA j has been exposed to the treatment for k years in year t. The parallel trends assumption holds if the leads in these models are jointly insignificant (Autor 2003, Rietveld et al. 2019). Observing the lags of this relative time model can further inform how the posttreatment effect evolved. Figure 2 shows the parallel trends for the overall sample, the *IT-using* CVC subsample, and the *IT-producing* CVC subsample separately, and Online Appendix Table C2 shows the coefficient estimates of the relative time model. The pretreatment trends across all models are jointly insignificant, ensuring that the parallel trends assumption holds. In the posttreatment periods, dissimilar investments, especially those made by *IT-using CVCs*, are positive and significant, whereas similar investments remain largely unchanged.

3.3.4. Staggered Treatment. In recent years, there has been rapid development of econometric methods to address potential biases associated with two-way fixed effects estimation in difference-in-differences studies with staggered treatment assignment. To ensure robust and reliable causal inference, we employed advanced estimators developed by Callaway and Sant'Anna (2021). Specifically, we utilized the doubly robust difference-in-differences with inverse probability weighting estimator within the Callaway and Sant'Anna (2021)'s *DiD* framework (*CSDiD*). As a robustness check, we also employed the Borusyak et al. (2024) estimator (BJS estimator) as an alternative estimator, which offers improved efficiency in the estimation process. The BJS estimator addresses staggered treatment adoption by imputing counterfactuals for each treatment group. These methodologies also offer robust inference by accounting for potential biases associated with time-varying treatment effects and unobserved confounders. For the main model, we present results using *CSDiD* and the traditional TWFE model. For subsequent analyses involving heterogeneous treatment effects or models with triple difference specification, we rely on the TWFE model because these features are still under development in the modern econometric methods.

3.3.5. Clustering of Standard Errors. Determining the appropriate level of clustering for standard errors requires careful consideration of the data-generating process (Abadie et al. 2023). In our setting, we are interested in individual CVCs' investment behavior changes after accelerators' entry into an MSA, and the data-generating process that we believe most plausible is: (1) each CVC is allocated a budget to invest in year t; (2) the CVC looks at a portfolio of MSAs (for example, the locations that it has prior relationships/investments historically) and decides where to invest; and (3) some MSAs within the CVC's portfolio are treated with accelerator entries, and the treated MSAs receive increased attention from the CVC. Under this data-generating process, the error terms are likely correlated at the CVC level after controlling for common shocks at the MSA-CVC level through fixed effects, as CVCs likely make independent investment decisions. That is, although the accelerator entry may increase investor interest in a region, after controlling for MSA-CVC level common shocks, the CVC's ultimate investment decision is driven by CVC-specific factors, such as geographical location, industry specialization, and investor networks (e.g., Sorenson and Stuart 2001, Fritsch and Schilder 2008).[16] Although we believe that CVC-level clustering is a more accurate reflection of the data-generation process, we present results for three different levels of clustering—CVC, CVC-MSA, and MSA—in our main analysis to allow readers to assess the robustness of our findings.

4. Main Results

4.1. Investment Strategies of CVCs: Investment Amounts in Similar and Dissimilar Startups

Table 3 presents the estimation results of Equation (1), estimated using the Callaway and Sant'Anna (2021) estimator with a doubly robust estimation method and wild cluster bootstrapped standard errors (Cameron et al. 2008) across three levels of clustering (i.e., CVC, CVC-MSA, and MSA level). Across all clustering levels, CVCs do not make notable changes to their investment strategies in *similar* startups (column (1)). However, they significantly increase their investments in *dissimilar* startups, as shown in column (2) across all panels. The coefficient of 0.032 corresponds to an increase of 3.25% (exp(0.032) − 1 = 3.25%), or about \$36,780 at a mean value of \$1.131 million in dissimilar investments

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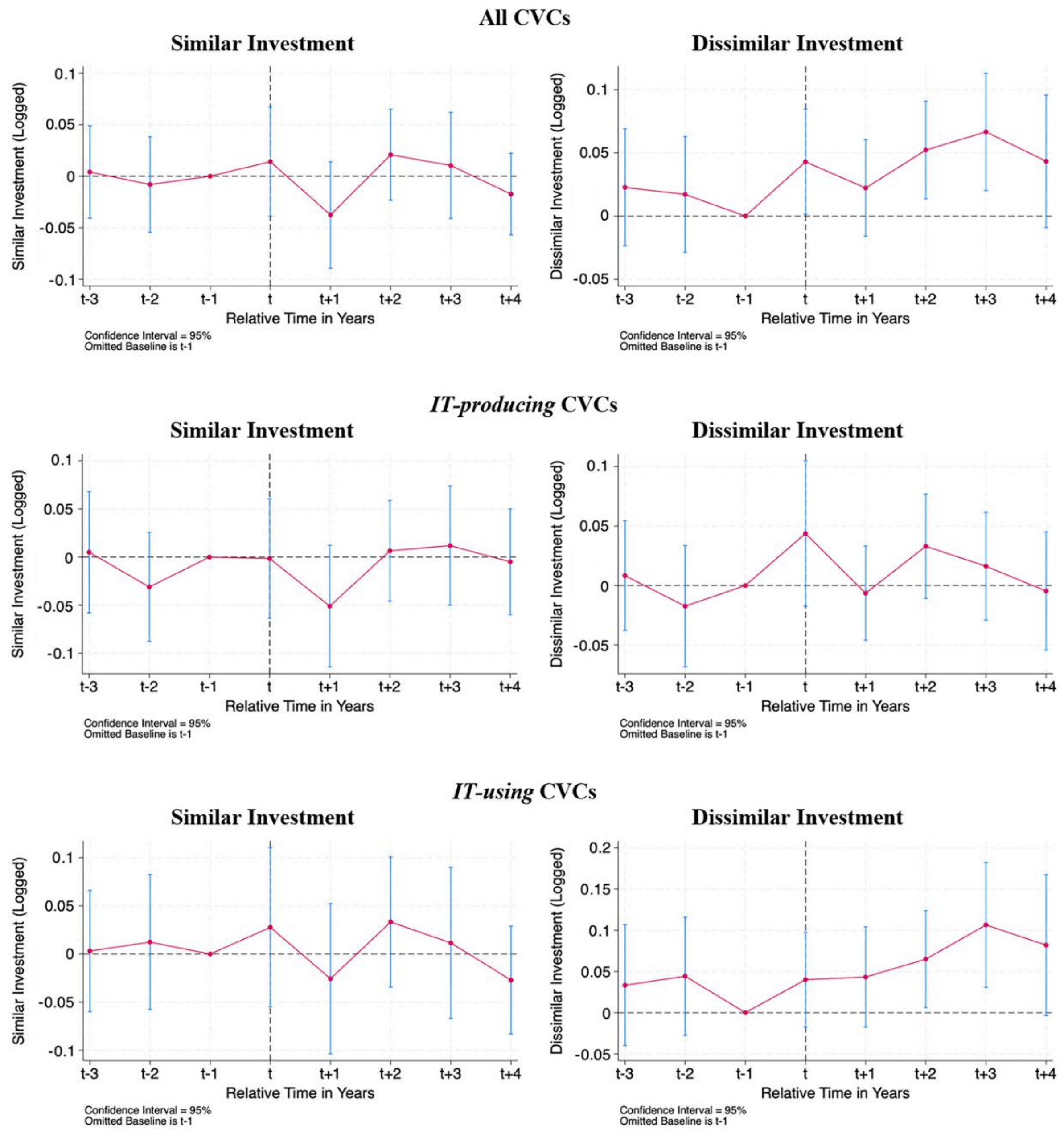
Figure 2. (Color online) Parallel Trends Graphs



(3.25% of \$1.131 million = \$36,780). When we bifurcate the CVCs into *IT-producing* and *IT-using* subsamples, this change in investment pattern is salient only in the *IT-using* CVC subsample (column (6)), with an implied increase of 3.87%, or \$43,805. Meanwhile, *IT-producing* CVCs do not display the same change in their investment strategy (column (4)).

Table 4 shows the TWFE estimation results. The *DiD* estimate in column (1) shows that CVCs do not alter their investment strategies in *similar* startups. The investment amount in startups that are *dissimilar* to a CVC's core business, on average, increases by 1.21% ($\exp(0.012) - 1 = 1.21\%$), or \$13,685, as shown in Table 4, column (2). Consistent with prior analysis, the *IT-producing CVCs* and *IT-using* CVCs react differently in their *dissimilar* investment strategies. Whereas *IT-producing* CVCs do not alter their *dissimilar* investment strategies (column (4)), *IT-using* CVCs significantly increase their investments in *dissimilar* startups (column (6)) by 2.74%, amounting to \$30,989. Column (8), which incorporates the triple-difference specification from Equation (2(b)), also indicates that any change in the investments by *IT-producing* CVCs in *dissimilar* startups is negligible, whereas investments by *IT-using* CVCs increase by

Table 3. Investment Strategies of CVCs—Estimated Using the Callaway and Sant'Anna DiD

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	*All CVC firms*		*IT-producing CVC SubSample*		*IT-using CVC SubSample*	
Dependent variable	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)
Estimation method	Callaway and Sant'Anna DiD (not-yet-treated as control)					
	Panel A: Clustering the standard errors at CVC level					
$treated_{ij} \times post\_entry_{jt}$	0.024	0.032**	0.041	0.017	0.004	0.038*
90% CI	[−0.010, 0.058]	[0.010, 0.053]	[−0.000, 0.082]	[−0.005, 0.040]	[−0.042, 0.050]	[0.004, 0.071]
95% CI	[−0.015, 0.063]	[0.005, 0.058]	[−0.007, 0.089]	[−0.009, 0.044]	[−0.049, 0.058]	[−0.002, 0.077]
Observations	49,854	49,854	21,756	21,756	28,098	28,098
	Panel B: Clustering the standard errors at CVC-MSA level					
$treated_{ij} \times post\_entry_{jt}$	0.024	0.032*	0.041	0.017	0.004	0.038*
90% CI	[−0.011, 0.059]	[0.004, 0.059]	[−0.006, 0.088]	[−0.018, 0.053]	[−0.040, 0.050]	[0.000, 0.076]
95% CI	[−0.016, 0.064]	[−0.001, 0.064]	[−0.013, 0.095]	[−0.024, 0.058]	[−0.049, 0.058]	[−0.008, 0.083]
Observations	49,854	49,854	21,756	21,756	28,098	28,098
	Panel C: Clustering the standard errors at MSA level					
$treated_{ij} \times post\_entry_{jt}$	0.024	0.032**	0.041	0.017	0.004	0.038**
90% CI	[−0.005, 0.053]	[0.009, 0.054]	[−0.002, 0.084]	[−0.018, 0.052]	[−0.037, 0.046]	[0.006, 0.069]
95% CI	[−0.010, 0.058]	[0.005, 0.058]	[−0.009, 0.090]	[−0.022, 0.057]	[−0.044, 0.054]	[0.001, 0.074]
Observations	49,854	49,854	21,756	21,756	28,098	28,098

Note. Confidence intervals [in square brackets] are computed using the Wild Cluster Bootstrap procedure.
*CI 90% does not include 0; **CI 95% does not include 0.

2.74%. Online Appendix Table C3 presents the TWFE results using clustering at the MSA-CVC, which align with the main results, and at the MSA level, where they become insignificant, indicating a need for caution in interpreting the results from the TWFE models based on the clustering method and the underlying data-generating process.

4.2. Detailed Investment Analysis

To further investigate the pattern changes, we split the CVC investments in our data set into four quartiles based on the business relatedness of all the CVC-startup pairs: very low similarity investments (0%–25% cosine similarity), low similarity investments (25%–50% cosine similarity), high similarity investments (50%–75% cosine similarity), and very high similarity investments (75%–100% cosine similarity). We then aggregated these investments at the CVC-MSA level for each year. This approach allows the analysis of changes in investment strategies in the four quartiles, instead of a simple similar/dissimilar bifurcation. Table 5 presents the results of this analysis.

Table 4. Investment Strategies of CVCs–Estimated Using the Traditional TWFE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	*All CVC firms*		*IT-producing CVC SubSample*		*IT-using CVC SubSample*		*Triple-difference with all CVC firms*	
Dependent variable	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)
Estimation method	TWFE DiD (not-yet-treated as control)							
$treated_{ij} \times post\_entry_{jt}$	−0.004	0.012*	−0.000	−0.005	−0.006	0.027***	−0.006	0.027***
	(0.007)	(0.006)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)
$treated_{ij} \times post\_entry_{jt} \times IT\_producing\_CVC_i$							0.007	−0.031**
							(0.014)	(0.012)
CVC-MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,854	49,854	21,756	21,756	28,098	28,098	49,854	49,854
R^2	0.230	0.220	0.287	0.242	0.180	0.213	0.230	0.221

Notes. Standard errors clustered around the CVC firm are in parentheses. All controls are used, but not shown for brevity.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 5. Investment Strategies of CVCs–Quartile Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	log(*similarity very_low*)		log(*similarity low*)		log(*similarity high*)		log(*similarity very_high*)	
Estimation method	TWFE DiD (not-yet-treated as control)							
$treated_{ij} \times post\_entry_{jt}$	0.003	0.012*	0.008*	0.019***	−0.002	−0.005	−0.006	−0.005
	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.006)	(0.007)
$treated_{ij} \times post\_entry_{jt} \times IT\_producing\_CVC_i$		−0.021**		−0.022**		0.008		−0.002
		(0.010)		(0.009)		(0.010)		(0.011)
CVC-MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,854	49,854	49,854	49,854	49,854	49,854	49,854	49,854
R^2	0.162	0.162	0.156	0.156	0.162	0.163	0.163	0.163

Notes. Standard errors clustered around the CVC firm are in parentheses. All controls are used, but not shown for brevity. Very low = 0%–25%; Low = 26%–50%; High = 51%–75%; very high = 76%–100% similarity.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The increase in investment is most salient in startups that have *low* similarity to the CVC (column (3)), but not those with *high* (column (5)) or *very high* similarity (column (7)). When we add three-way interactions in the even-numbered columns, the increases in *very low-similarity* (column (2)) and *low*-similarity (column (4)) investments by *IT-using* CVCs are significantly greater compared with *IT-producing* CVCs. Marginal effect calculations suggest that *IT-producing* CVCs do not increase their investments in either *low-similarity* or *very low-similarity* groups. An interesting observation is that among *IT-using* CVCs, we observe a greater marginal effect on the *low*-similarity group (0.019, column (4)) than on the *very low*-similarity group (0.012, column (2)), consistent with the results of main models presented in columns (1) and (3). It is likely that, with extremely low similarity, a startup has little overlapping knowledge with the CVC, leading to a diminished absorptive capacity for the CVC (Cohen and Levinthal 1990). In summary, after an accelerator begins its operation, *IT-using* CVCs demonstrate a higher investment preference in less similar startups, whereas *IT-producing* CVCs do not significantly alter their investment strategies.

5. Robustness Tests

We performed a series of tests to ensure that our findings are robust to various model specifications, different measurements of the key variables, and sample matching techniques.

5.1. Alternative Model Specifications

The body of research on Difference-in-Differences methods with staggered treatment is rapidly evolving. For example, Callaway and Sant'Anna (2021) propose a technique based on inverse probability weighting and regression adjustment, whereas Borusyak et al. (2024) recommend an imputation-based approach that focuses on untreated units with similar treatment timing. Sun and Abraham (2021) offer yet another alternative based on a TWFE model with interacted event-time indicators. Considering these diverse methodologies and their distinct underlying assumptions, we conducted robustness checks to assess the consistency of our results under different approaches.

Our first robustness check employs the alternative matching and causal inference technique, as outlined by Borusyak et al. (2024), with results presented in Online Appendix Table C4. Panels A–C present the results across three levels of clustering: CVC, CVC-MSA, and MSA. The estimates across all three panels show a similar pattern, with only dissimilar investments for *IT-using* CVCs growing by 3.8%, translating to an increase of $42,978 per CVC-MSA-year, based on a mean value of $1.131 million.

To further ensure that our findings are not driven by specific modeling choices, we estimated the effects using the methods proposed by Gardner (2022), Sun and Abraham (2021), and Roth and Sant'Anna (2023). The results from these estimators are visualized alongside Callaway and Sant'Anna's (2021) estimator in Online Appendix Figure C1, generated using the *event_study()* function from the *did2s* package by Butts and Gardner (2022). These results consistently show that the change in investment strategies is primarily driven by *IT-using* CVCs investing in *dissimilar* startups, further supporting our main findings.

Next, recognizing that investment amounts across the two equations of (1(a)) and (1(b)) may be correlated because of the resource constraints faced by the CVCs in any given year, we simultaneously estimated them using a Seemingly Unrelated Regression specification. This approach allows for the disturbances of the two equations to be correlated, potentially improving the efficiency of our estimates. The results, presented in Online Appendix Table C4, Panel D, remain consistent with our main findings.

Finally, to further ascertain that the method of clustering the standard errors does not drive the outcomes, we bootstrapped the standard errors in line with the literature on matching without replacement (Smith and Todd 2005, Austin and Small 2014). We estimated the models and then bootstrapped the standard errors based on 100 replications. The results are presented in Online Appendix Table C4, Panel E. The results remain consistent with the main findings, revealing that the only change in the investment strategy involves *IT-using* CVCs shifting toward *dissimilar* startups.

5.2. Alternative Measurements

5.2.1. Alternative Measurement of the Dependent Variable: Overall Investments. Instead of separately analyzing the impact on investments in *similar* and *dissimilar* startups, we pooled the *similar* and *dissimilar* investments together to study if the overall investment amount of a CVC increases after the treatment, similar to IVCs as shown by prior studies (e.g., Fehder and Hochberg 2014). Online Appendix Table C5 illustrates the impact of the accelerator's entry on the overall investment amount by CVCs. Consistent with extant literature, we find that overall investments increase after the accelerator entry (column (1)), but this increase is predominantly driven by *IT-using CVCs* (as highlighted in column (3)).

5.2.2. Alternative Measurement of the Treatment Variable. Although the use of a binary treatment variable allows for identifying the treatment effect through a *DiD* design, leveraging the number of startups that are accelerated in an MSA-year could capture the effect of accelerators at a more granular level. In this exercise, we replaced the *post_entry* dummy variable (which captures accelerator entry) with the number of startups that were accelerated in the MSA-year. We applied a log-transformation to this variable by adding one because of its skewed distribution and re-estimated the model by introducing an interaction term between this continuous variable and the *treated* variable. The results, presented in Online Appendix Table C6, show that doubling the number of accelerated startups corresponds to a 1.0% increase in the *dissimilar* investment by *IT-using* CVCs, a result qualitatively consistent with our main analysis.

5.2.3. Alternative Classifications of Similar and Dissimilar Investments. Our key analyses show that accelerators help CVCs achieve their strategic objectives by aiding them to invest in startups that are less similar to their parent companies. To ensure that the findings are not driven by potential mismeasurement of *similar* and *dissimilar* investments, we followed a two-pronged strategy: one involving an analysis of the sensitivity of this bifurcation, and the other exploring alternative methods of constructing business-relatedness measures.

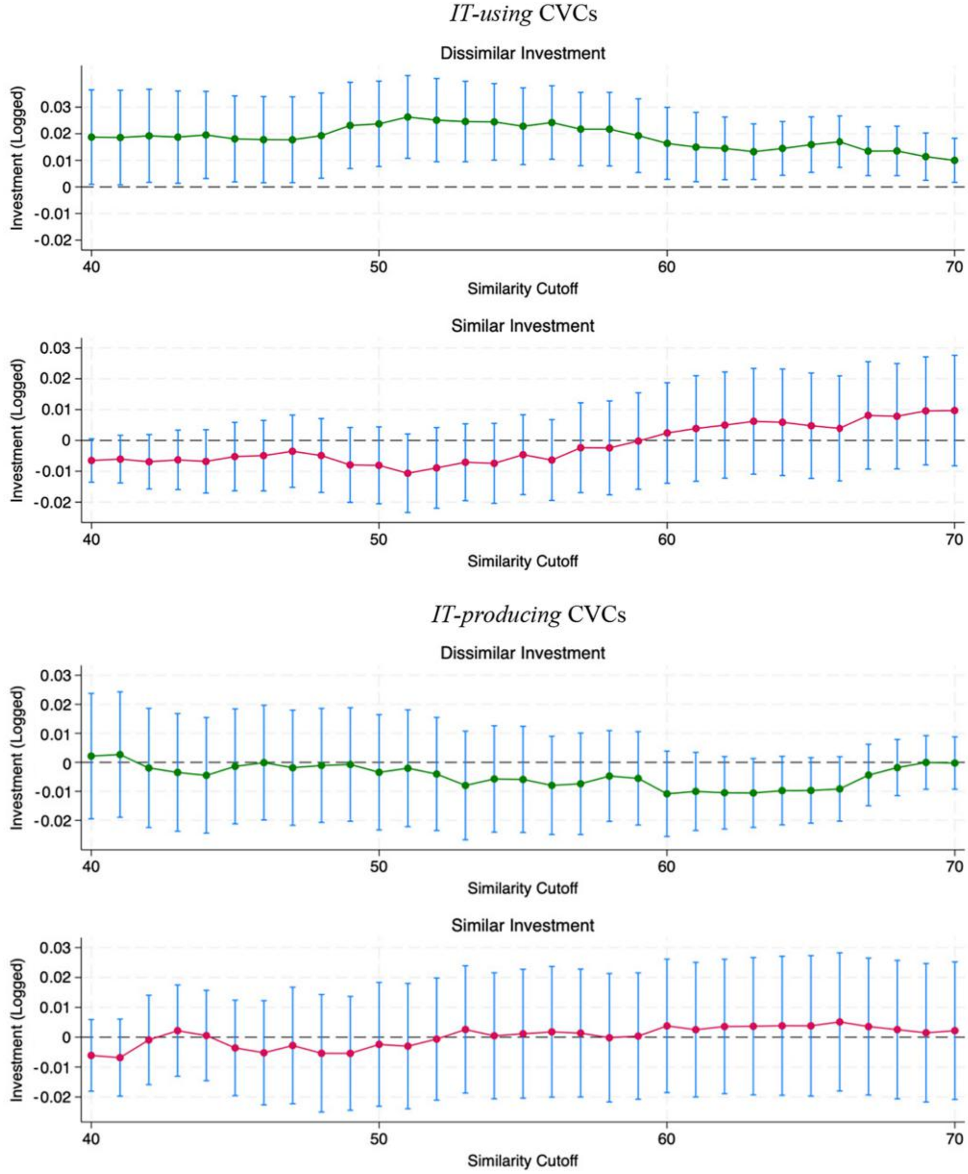
5.2.3.1. Sensitivity Test. We tested the sensitivity of our findings to the cut-off value used for segmenting investments as *similar* or *dissimilar*[17] (i.e., using the median value of 56.25), as previously described in Section 3.2.1.2. Specifically, we varied the cutoff value from 40 to 70 in increments of 1 and plotted the corresponding effect sizes of the *DiD* estimates in a single graph (Figure 3). This graph helps ascertain whether our chosen threshold affects the outcome of our model estimation. We find that results remain remarkably consistent across the tested cut-off range: the increase in the investment is statistically significant only for *IT-using* CVCs when investing in *dissimilar* startups.

Another sensitivity test we performed involves the sources from which we obtained startups' business descriptions. Recall that we supplement a startup's business description from VentureXpert with its Crunchbase profile whenever available. Because about a third of startups in our sample lacked Crunchbase profiles, we recomputed the business similarity using only VentureXpert as the source for descriptions. Based on this new measure, we bifurcated the investments into *similar* and *dissimilar*, re-estimated the models, and present the results in Online Appendix Table C7. The results, once again, are consistent.

5.2.3.2. Alternative Ways of Measuring Business Relatedness. We employed two alternative measures to assess the business relatedness between startups and CVC investors—(1) a NAICS-based business relatedness score through manual tagging of startups, and (2) a Topic Modeling-based similarity score (Shi et al. 2016). First, extant research has used the NAICS code of public firms to measure business relatedness (Bhojraj et al. 2003). However, because startups lack NAICS codes, we manually determined their NAICS codes with assistance from Research Assistants (RAs). We provided RAs with explicit instructions for determining the four-digit NAICS code for startups, from which we extracted the two-digit NAICS code for each startup. The interrater reliability between the two RAs was about 82%.[18] In case of a disagreement between the two RAs, we hired a third RA to break the tie. This process provides us with a reliable measure of NAICS codes. Next, we obtained two-digit NAICS codes for CVCs from the Compustat database. Investments were classified as *similar* if the investing CVC and the startup shared the same two-digit NAICS code, and as *dissimilar* otherwise. We reran the entire analysis using the new measurement of *similar* and *dissimilar* investments. As shown in Online Appendix Table C8, we find consistent results.

Second, we followed Shi et al. (2016) and computed a similarity score between an investing CVC firm and a startup based on the topics derived from their business descriptions. In simple terms, this method involves determining the document-topic distribution for each

Figure 3. (Color online) Plotting the *DiD* Estimate by Varying the Cutoff Similarity Value for Separating Similar/Dissimilar Investments from 40% to 70%



Note. Vertical lines around the point estimates represent a 95% confidence interval.

text (i.e., firm description) and then using them to measure the cosine distance between texts across each topic dimension. A key task is to determine the count of topics, a parameter required as input for the model. Following the literature, we evaluated the topic coherence and determined that 14 topics achieved the highest coherence (Online Appendix Figure C2). Consequently, we assessed the document-topic distribution for each of the text descriptions in our analysis and then computed the cosine distance between each of the topic distributions of the CVC and the respective startup. We then bifurcated the investments into *similar* and *dissimilar* investments based on the median value of this similarity score, which is consistent with our main analysis. The results are presented in Online Appendix Table C9. Once again, these results are consistent with our main analysis.

5.2.4. Alternative Measurement of Control Variables. The subsequent robustness check addresses the handling of missing R&D and SG&A values (recall that SG&A is needed for calculating coordination investment) in Compustat. Prior studies have addressed missing R&D or SG&A expenses by replacing the missing values with zero (Dyreng et al. 2010, Servaes and Tamayo 2013). To mitigate concerns caused by such replacement, we re-estimated our models by excluding observations with missing R&D and coordination investment amounts. The results, reported in Online Appendix Table C10, show that the outcomes remain qualitatively consistent.

5.3. Alternative Parametric Matching

The main analysis uses the "not-yet-treated" observations as the control group. In this section, we employed a stricter matching method, where each treated CVC also serves as a control for itself in the matching process. That is, we hold the CVC constant and only change the MSA in the matching process, with the treated observations experiencing accelerator entry and control observation not witnessing an entry until the end of the panel. However, imposing the restriction that the treated and control units should have the same CVC, but have different MSAs, leads to a significant reduction in the number of observations. This limitation arises because of the limited availability of locations where CVCs make investments, such that one location experiences an accelerator entry, whereas the other comparable location does not. Consequently, selecting suitable locations that satisfy this specific criterion becomes significantly constrained. Nonetheless, we performed this new matching using the stricter matching criterion and re-estimated the model. The results, presented in Online Appendix Table C11, remain qualitatively consistent.

5.4. Other Robustness Checks

The final set of robustness checks examines accelerator exits as a reverse shock. To analyze the impact of accelerator exits, we introduced an interaction term comprising two dummy variables: *treated_accelerator_exit*, which identifies treated units that experienced an accelerator exit, and *post_exit*, which is assigned a value of one for years following the exit. It should be noted that the observations where *treated_accelerator_exit* = 1 is a subset of those with *treated* = 1. The results are presented in Online Appendix Table C12. The estimated effect of this interaction term is negative and significant, consistent with the intuition that accelerator exits lead to reduced *dissimilar* investments from CVCs in subsequent years.

6. Mechanism Analyses

Our analyses so far show that *IT-using* CVCs increase their investments in *dissimilar* startups after accelerators' entry. This finding can be explained by one of two reasons: (1) by aggregating startups in their cohorts, the entry of an accelerator increases the supply of high-tech startups (which are *dissimilar* to *IT-using* CVCs) in a region and reduces search costs for CVCs (we call it *the startup supply* hypothesis); or (2) through the screening during the admission process, as well as the mentorship and training it provides, an accelerator helps reduce information asymmetry, and the service is more valuable for *IT-using* CVCs because they, unlike *IT-producing* CVCs, are not familiar with the high-tech space (we call it *the information asymmetry* hypothesis). The *startup supply* hypothesis is plausible, given that most startup accelerators have a large fraction of participating startups from the IT sector (Crișan et al. 2021), and the advent of an accelerator likely increases the supply of IT startups in the region, leading to increased investments by *IT-using* CVCs in IT startups, which are in industry sectors *dissimilar* to their own. However, if this interpretation is the entire story, it fails to explain why there is no corresponding increase in *similar* investments (i.e., in IT startups) by *IT-producing* CVCs. Therefore, it appears that the reduction of information asymmetry at least partially plays a role in the CVCs' investment strategy changes. In the following section, we present additional evidence that lends further support to the latter explanation.

There are two ways in which accelerators may contribute to the reduction of information asymmetry: through mentorship and training, so that startups are better able to develop, articulate, and position their innovation to potential investors (the direct way); and through the screening process, in which accelerators lend legitimacy to participating startups and provide a quality signal (the indirect way) (Pauwels et al. 2016). We conduct three mechanism tests to demonstrate that both effects are likely present.

6.1. Training and Mentorship

Training and mentorship that help startups discover their core offering and pitch their idea should benefit *IT-using* CVCs to a greater extent than *IT-producing* CVCs. Given their familiarity with the high-tech domain, *IT-producing* CVCs are better equipped than *IT-using* CVCs to assess and evaluate the quality of high-tech startup ideas, even in the absence of startup accelerators. Therefore, we exploit heterogeneities in accelerators' mentorship styles for this mechanism analysis. In this test, we focus on the accelerators' cohort duration. We argue that the longer the cohort duration, the greater the amount of mentorship and training the participating startups will receive, and therefore, the higher the likelihood of resolving the uncertainty surrounding a startup's core offering. We created a dummy variable, *CohortDuration_Long*, which carries the value of one if, in any year t, there is at least one accelerator in MSA j with a cohort duration longer than the median (of 90 days). Table 6, columns (1)–(4) show the result of the model estimation with a three-way interaction involving the *DiD* variables and the cohort duration dummy. Columns (1) and (2) suggest that a longer cohort duration does not affect the way that accelerator entry influences investment amounts by *IT-producing* CVCs. In contrast, column (4_ shows that a longer cohort duration positively moderates the effect of accelerator entry on the *dissimilar* investment amounts by *IT-using* CVCs. To test the robustness of our definition of "longer

Table 6. Mechanism Analysis–Cohort Length

Definition of long cohort	Cohort length greater than 90 days (above median)				Cohort length greater than 107 days (top quartile)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	*IT-producing CVC SubSample*		*IT-using CVC SubSample*		*IT-producing CVC SubSample*		*IT-using CVC SubSample*	
Dependent variable	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)
Estimation method	TWFE DiD (not-yet-treated as control)							
$treated_{ij} \times post\_entry_{jt}$	−0.002	−0.004	−0.014	0.004	−0.005	−0.002	−0.015	0.009
	(0.010)	(0.010)	(0.012)	(0.013)	(0.007)	(0.008)	(0.010)	(0.010)
$treated_{ij} \times post\_entry_{jt}$	0.011	−0.001	0.003	0.031*	0.015	−0.004	0.010	0.034*
$\times$ $CohortDuration\_Long_{jt}$	(0.019)	(0.017)	(0.017)	(0.017)	(0.020)	(0.019)	(0.019)	(0.019)
CVC-MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,756	21,756	28,098	28,098	21,756	21,756	28,098	28,098
R^2	0.288	0.242	0.181	0.213	0.287	0.242	0.180	0.213

Notes. Standard errors clustered around the CVC firm are in parentheses. All controls are used, but not shown for brevity.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

cohort," we changed the definition of a long cohort to any cohort duration greater than the top quartile (of 107 days) in any year t. The results of this analysis are presented in Table 6, columns (5)–(8). The results are similar to each other and are consistent with the *information asymmetry* hypothesis, which posits that mentorship and training help reduce the uncertainty about startups' core offerings, which benefits *IT-using* CVCs more than *IT-producing* CVCs. However, they do not align with the *startup supply* hypothesis, which suggests that the increase in *dissimilar* investments is because of an increase in the supply of high-tech startups associated with an accelerator's entry.

6.2. Signals of Quality

The second way in which accelerators may help reduce information asymmetry is through the quality signals they provide for the startups that pass their rigorous screening process. We argue that the signal of quality is stronger if the accelerator is willing to put money where its mouth is by investing in its cohorts of startups. Many accelerators provide seed funding to the startups they admit in exchange for a small fraction of their equity (typically around 5%–8%). There are some accelerators, however, that do not require startups to dilute their equity to participate. Given these incentive differences, we hypothesize that the impact of a non-equity-based accelerator on reducing information asymmetry should be relatively lower than equity-based accelerators. To compare the impact of the entry by an equity-based accelerator with that of a non-equity-based one, we tagged all accelerators as equity-based or non-equity-based using the information provided by Seed-DB. We then created two dummy variables: *post_entry_nonequity*, which carries a value of one after the first non-equity-based accelerator starts its operations in the MSA; and *post_entry_equity*, which carries a value of one after the first equity-based accelerator starts its operations in the MSA. We introduced the two interaction terms by interacting the *treated* variable with the above two variables in Equations (1(a)) and (1(b)) and subsequently re-estimated the models. The results, presented in Table 7, suggest that only the entry of an equity-based accelerator alters CVCs' investment strategy in *dissimilar* startups, again confirming the *information asymmetry* hypothesis, but contradicting the *startup supply* hypothesis.

6.3. CVC Parent IT Intensity

We argue that if accelerators indeed help mitigate information asymmetry for investors interested in high-tech startups, their services will have the greatest impact on CVCs that have the least competence in screening those startups (e.g., Aggarwal et al. 2015) before their entry. A CVC whose parent company is in the IT industry (e.g., Microsoft) likely already possesses strong competence in evaluating high-tech startups, even without relying on accelerators. In contrast, a CVC whose parent company belongs to *IT-using* industries (e.g., Exxon) is typically less equipped with the expertise to assess the quality of high-tech startups and, therefore, stands to benefit more from the entry of accelerators.

We further extend this reasoning and hypothesize that even among *IT-using* CVCs, some CVCs may have a parent firm making significant IT investments, and, therefore, such CVCs are likely to have stronger competencies in screening high-tech startups before the entry of accelerators. In other words, if there is a positive correlation between a CVC's competence in screening high-tech startups and its parent's investment in IT, then the degree to which a CVC benefits from the

Table 7. Mechanism Analysis–Impact of Non-Equity-Based Accelerators

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	*All CVC Firms*		*IT-producing CVC SubSample*		*IT-using CVC SubSample*	
Dependent variable	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)
Estimation method	TWFE DiD (not-yet-treated as control)					
$treated_{ij}$ × $post\_entry\_equity_{jt}$	−0.003	0.009*	−0.004	−0.003	−0.002	0.020**
	(0.006)	(0.006)	(0.009)	(0.008)	(0.009)	(0.008)
$treated_{ij}$ × $post\_entry\_nonequity_{jt}$	−0.027	−0.026	0.001	−0.084	−0.065	0.039
	(0.033)	(0.040)	(0.045)	(0.058)	(0.058)	(0.045)
CVC-MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,854	49,854	21,756	21,756	28,098	28,098
R^2	0.230	0.220	0.287	0.242	0.180	0.213

Notes. Standard errors clustered around the CVC firm are in parentheses. All controls are used, but not shown for brevity.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

services of accelerators should be inversely correlated with the IT intensity of its parent firm. Therefore, an *IT-using* CVC with a high IT-intensity parent firm will experience fewer investment pattern changes after the entry of an accelerator.

For this analysis, we obtained the measure of IT intensity for CVC parent firms following prior literature, which commonly defines IT intensity as the ratio of IT capital to total capital (e.g., Brynjolfsson and Hitt 2003, Acemoglu et al. 2014, Huang et al. 2022). Specifically, we used IT intensity data at the four-digit NAICS industry level from Huang et al. (2022), who utilized the CII database to compute the IT capital and IT intensity of Fortune 1000 firms. Given that over 40% of the CVCs in our data set are not Fortune 1000 firms, we adopted the industry-level IT intensity as a proxy for the IT intensity of CVC parent firms.

Econometrically, we introduced a three-way interaction involving *treated*, *post_entry*, and the *IT_intensity* variable in Equations (1(a)) and (1(b)) and re-estimated the models. The results are presented in Table 8. Columns (1), (3), and (5) suggest that the IT intensity of a CVC does not significantly moderate the effect of accelerator entry on its *similar* investment amount. Column (2) indicates that the IT intensity of a CVC negatively moderates the effect of accelerator entry on its investment amount in *dissimilar* startups. Subsample analysis further reveals that, among *IT-producing* CVCs, IT intensity does not moderate the effect of accelerator entry on a *dissimilar* investment amount (column (4)). In contrast, among *IT-using* CVCs, IT intensity negatively moderates the effect of accelerators' entry on a *dissimilar* investment amount (column (6)). The finding that accelerator entry primarily affects investments in *dissimilar* startups

Table 8. Mechanism Analysis–IT Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	*All CVC Firms*		*IT-producing CVC SubSample*		*IT-using CVC SubSample*	
Dependent variable	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)	log(*similar amount*)	log(*dissimilar amount*)
Estimation method	TWFE DiD (not-yet-treated as control)					
$treated_{ij}$ × $post\_entry_{jt}$	0.006	0.027***	0.018	0.009	−0.001	0.039***
	(0.010)	(0.009)	(0.012)	(0.013)	(0.014)	(0.012)
$treated_{ij}$ × $post\_entry_{jt}$ × $IT\_Intensity$	−0.162	−0.241**	−0.243	−0.191	−0.097	−0.228*
	(0.128)	(0.099)	(0.169)	(0.137)	(0.144)	(0.122)
CVC-MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49,854	49,854	21,756	21,756	28,098	28,098
R^2	0.230	0.220	0.287	0.242	0.180	0.213

Notes. Standard errors clustered around the CVC firm are in parentheses. All controls are used, but not shown for brevity. *IT intensity* is a continuous variable in the three-way interaction.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

by CVCs with low IT intensity further provides support to our *information asymmetry* hypothesis.

To test the marginal effect of IT Intensity, we employed the linear combination procedure to calculate the *DiD* estimate at various values of IT intensity. The results, presented in Online Appendix Table C13, Panel A, show that the effect of the accelerator entry on *dissimilar* investments remains positive and significant at the 25th percentile, median, and 75th percentile, and becomes insignificant only at the 90th percentile. In contrast, the impact of accelerator entry on *similar* investments stays insignificant across all values of IT intensity, providing support to our argument. We further test the robustness of our analysis by conducting the analysis using the firm-level measure of IT intensity instead of the industry-level measure. This restricts our sample to CVCs that are Fortune 1000 firms, comprising about 57% of the full sample. The results, presented in Appendix Table C13, Panel B, are consistent with our main analysis as well.

7. Discussion and Conclusions

7.1. Key Findings and Discussion

We present a systematic empirical investigation into the question of how the entry of a startup accelerator impacts CVCs' investment patterns, particularly regarding the degree of business relatedness between their portfolio firms and their parent companies. Our analyses reveal several new insights. First, we show that following the entry of a startup accelerator in a region, CVCs, on average, increase their investments in startups *dissimilar* to their parent firm's business by amounts ranging from \$13,685 (based on the TWFE estimates in Table 4) to \$36,780 (based on *CSDiD* estimates in Table 3). In our data set, the mean count of investment deals per MSA-year by all CVCs is 5.2, with the top 5% of MSAs receiving 23 CVC investments, on average, in a year. Using the most conservative estimate from the TWFE model, this translates to an annual increase of \$71,162 (\$13,685 × 5.2) in CVC investments for an average MSA and approximately \$314,755 (\$13,685 × 23) annual increase for an MSA in the top 5%. The corresponding numbers from the *CSDiD* estimates are \$191,256 for an average MSA and \$845,940 for an MSA in the top 5%. The result suggests that startup accelerators, through their screening, mentoring, and coaching services, help mitigate the assessment and valuation problems that CVC investors face (Dushnitsky and Shapira 2010), making them more comfortable with investing in ventures they might typically avoid.

Interestingly, our analyses reveal a consistent pattern where *IT-using* CVCs increase investments in dissimilar startups following accelerator entry. This finding supports the notion that startup accelerators help *IT-using* CVCs better achieve their strategic goal of exploring a more diverse space of new technologies and establishing a foothold in the digital space, which can be particularly important in an era when nearly every *IT-using* industry is undergoing a digital transformation and disruption. At the same time, it highlights the fact that startup accelerators' effect on reducing information asymmetry is somewhat limited for *IT-producing* CVCs, perhaps because they are highly specialized in the high-tech space and therefore are capable of screening high-tech startups by themselves, even without the aid of accelerators.

Second, the mechanism analyses further lend support to our *information asymmetry* hypothesis as the explanation for the investment pattern changes. The first mechanism analysis suggests that the training and mentorship that accelerators provide is one plausible explanation for the reduction of information asymmetry. Accelerators with longer cohort durations, by providing a greater amount of training and mentorship, result in greater changes in *IT-using* CVCs' investment strategies. The second mechanism analysis suggests that the quality signals provided by accelerators may be another factor contributing to the reduction of information asymmetry. Equity-based accelerators are associated with a stronger-quality signal and therefore lead to more substantial changes in *IT-using* CVCs' investment strategies. Lastly, our third mechanism analysis suggests that, among *IT-using* CVCs, those whose parent companies have higher investments in IT benefit less from an accelerator's entry, likely because they are exposed to intensive use of technology and already possess strong competence in screening high-tech startups. In contrast, those CVCs whose parent companies have a lower IT intensity alter their investment patterns to a greater extent, likely due to the greater benefits they receive from accelerators' role as information intermediaries.

Together, these results provide a more comprehensive understanding of startup accelerators' impact on the entrepreneurial ecosystem. Beyond attracting more venture investments to the region, as shown in earlier studies (Fehder and Hochberg 2014), the entry of startup accelerators significantly alters the behavior patterns of venture investors. These behavioral changes have far-reaching implications for CVCs and their parent companies. For example, the theory of absorptive capacity (Cohen and Levinthal 1990) implies that a firm's ability to learn from external knowledge sources increases with the diversity of its knowledge base. Others also have shown that the rate of learning is higher with greater technological diversity (Schildt et al. 2012). Therefore, traditional patterns of CVC investments, such as investing primarily in closely related startup ideas, are arguably not ideal for their parent companies from a strategic perspective. Our finding that startup accelerators reduce information asymmetry for CVCs that traditionally lack the specialized expertise in the high-tech space suggests that they help CVCs better achieve their strategic objectives, particularly for those with parent firms undergoing digital transformations.

7.2. Contributions and Future Research

Our work makes several important contributions to the existing literature. First, it is well known that in the VC market, the assessment and valuation of startups suffer from considerable information asymmetry, such as adverse selection (Amit et al. 1990). Although investors in public companies can reduce the level of information asymmetry through corporate disclosure on the one hand and financial information intermediaries on the other (Healy and Palepu 2001), the tools available to VC investors are rather limited. This assessment and valuation problem has long hampered CVCs from obtaining their financial and nonfinancial objectives through venture investments, thereby limiting the types of startups they typically invest in. One of the primary reasons for CVC investments is that such investments provide early access to explorative knowledge, offering breakthrough opportunities that help firms gain competitive advantage (Schildt et al. 2005). However, such strategic objectives can only be achieved when the portfolio firms possess sufficient novel knowledge for the CVCs to explore. If CVCs predominantly invest in closely related portfolio firms, their learning will likely be more exploitative, yielding mostly incremental benefits. This challenge can be especially thorny with ventures that are outside of the core expertise of the CVC's parent firm. Our findings indicate that the starting of the operations of startup accelerators in a region leads to CVCs investing in a broad set of ventures that are less related to their parent company, thus helping CVCs optimize their investment portfolios to more effectively serve their strategic goals.

Second, the finding that *IT-using* CVCs, particularly those that historically have not made intensive IT investments, benefit the most from the entry of accelerators also sheds some light on the relationship between the digital transformation of traditional businesses (Vial 2019, Hanelt et al. 2021, Verhoef et al. 2021) and its implications for productivity (van Ark et al. 2008, Bloom et al. 2012). For example, earlier studies have documented the puzzle that over 1995–2004, both European countries and the United States experienced tremendous productivity acceleration in *IT-producing* sectors. However, European countries did not achieve the same level of spectacular productivity growth in sectors that *use* IT intensively, such as wholesale, retail, and financial services (van Ark et al. 2008). This suggests that U.S. firms managed to exploit IT for productivity gains better than their European counterparts (Bloom et al. 2012). One plausible explanation is that *IT-using* firms in the United States, through their CVC investments in IT startups, were able to gain early exposure to new technologies and subsequently leverage this exposure to enhance their business processes and management practices. The results from our study imply that, with the help of startup accelerators, even those *IT-using* firms that have not yet made intensive IT investments may be able to gain exposure to IT startups and emerging new technologies through their CVC investments. This could, in turn, accelerate the pace of their digital transformation and lead to productivity boosts.

Third, literature focusing on the institutional forms that help nurture technology startups has recently experienced a significant surge in research interest. This surge is driven by the emergence of new entities, such as startup accelerators and crowdfunding platforms. For example, the literature on startup accelerators has studied the characteristics of this institutional form and has explored relevant questions from the perspective of portfolio companies (Cohen 2013, Hochberg 2016, Gonzalez-Uribe and Leatherbee 2018, Hallen et al. 2019). However, a holistic understanding of the ways in which accelerators nurture the startup ecosystem cannot be achieved without studying their impact on investors. Therefore, our study complements existing research in this line of inquiry by demonstrating the impact of startup accelerators on the behavioral patterns of investors. In doing so, we also contribute to the discourse on policies and institutions that aim to promote the development of regional entrepreneurial ecosystems.

Our study can be extended in several ways. For example, a more comprehensive study that investigates the impact of an accelerator on overall VC investment activities in a region could also examine its impact on the investment patterns of independent VCs and angel investors. Additionally, our research considers the entry of the startup accelerator as the main explanatory variable but does not specifically incorporate characteristics about the startup accelerators, such as their historical performance, their reputation, or the area of expertise and specialization they possess. Future research could explicitly include accelerator-specific attributes to capture their heterogeneous effects on CVC investment activities. Furthermore, future research could explicitly account for the pivots and shifts in startups' business activities over time to understand the evolution of business relatedness between them and their investors. Finally, although our research shows that the entry of startup accelerators results in changes to a CVC's investment strategies and helps in gaining exposure in new technology spaces, future research could investigate how such changes will impact the long-term R&D performance and innovation outcomes of its parent company. We hope our work will ignite the sparks of interest in pursuing these potentially fruitful directions.

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Endnotes

1 Although the earliest CVC is over 100 years old (DuPont in 1914), CVCs in the modern form appeared in the 1960s.

2 See https://www.forbes.com/sites/valleyvoices/2017/02/14/corporate-vc-on-the-rise/#74604fcbbf20 (accessed January 28, 2025).

3 See https://pitchbook.com/profiles/company/41424-13#investors (accessed January 28, 2025).

4 See, for example, https://www.bcg.com/publications/2019/dawn-deep-tech-ecosystem.aspx (accessed January 28, 2025).

5 From https://www.seed-db.com/accelerators (accessed 28 January 2025) and from the homepages of *Y Combinator* and *TechStars*, two of the largest accelerators (both accessed January 28, 2025).

6 A tiny fraction of VentureXpert deals are recorded with zero investment amounts because of incomplete reporting. These deals are included in our control variable calculations.

7 Detailed business descriptions are obtained from Section 1A (post-2005) or Section 1 (pre-2005) of firms' 10-K filings.

8 The text lengths of different startups' descriptions are comparable. The business descriptions obtained from both VentureXpert and Crunchbase (whenever available) are of standard length.

9 The startup descriptions do not change over time in VentureXpert. The CVC 10-K descriptions change roughly about 2% over 10 years, on average, indicating a gradual pivot in business activities.

10 In Section 5.2.3.1, we present a sensitivity analysis by setting the cutoff value between similar and dissimilar investments to any value within the range of [40, 70] with an increment of 1.

11 Coordination investment is defined as the difference between the Sales, General and Administrative (SG&A) expenses and the R&D investment made by the firm.

12 Consistent with prior literature (Dyreng et al. 2010, Servaes and Tamayo 2013), the missing *R&D* or *SG&A* values (needed for computing *coordination_investment*) were replaced with zero.

13 This is a syndicate investment scenario where multiple investors share knowledge and invest capital to reduce information asymmetry while sharing risk and rewards. For example, if a CVC makes 10 investments, and 1 of those investments has a co-investor, the value would be 0.1 (average of 1.1 co-investors per deal minus 1, i.e., itself).

14 Not every CVC invests in every region. The investment decisions are based on many factors, including physical distance (Fritsch and Schilder 2008) and personnel social network (Sorenson and Stuart 2001), among others. In our data set, the median investment distance between an investor and an investee is 960 miles and the 25th percentile is under 300 miles, suggesting that most investments happen within a two-hour flight distance.

15 The use of SUR also allows us to test whether β_2^s and β_2^d are systematically different using post hoc contrast tests, accounting for the fact that "the disturbances in the micro-regressions are correlated" (Zellner 1963, p. 355).

16 Alternative clustering levels could be considered, such as the *CVC-MSA* level if CVC's investment decisions are thought to be influenced by unique factors at the CVC-MSA combination, or the *MSA* level if treatment assignment at MSA level is believed to induce correlated shocks across all CVCs investing in that region.

17 We thank an anonymous reviewer for this suggestion.

18 The bulk of the disagreement was in biotech and healthcare because many of the healthcare startups straddle services (NAICS in 60s), manufacturing (NAICS 30s), and data analytics (NAICS 50s).

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