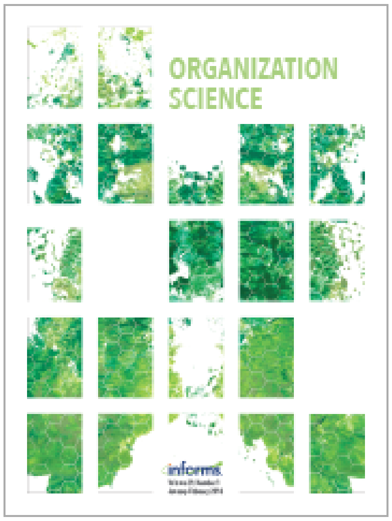

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On Resource Complementarity Among Startups, Accelerators, and Financial Investors: A Large-Scale Analysis of Sorting and Value Creation

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Abstract. We propose a theoretical framework and provide empirical evidence on how resource complementarity or substitutability between entrepreneurs and seed investors drives selection and value creation in the context of high-tech startups. Specifically, we argue that seed investors specialized in training programs—startup accelerators—are the ideal match for entrepreneurial teams equipped with strong technological competencies but lacking business knowledge. On the other hand, when entrepreneurs with extensive business knowledge pair up with accelerators, the value created is typically less. Combining information from Crunchbase and LinkedIn, we provide robust empirical evidence based on the assortative matching of start-ups and investors and the ex- post analysis of joint value creation.

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Keywords: accelerators • resource complementarity • entrepreneurship • technology startups • startup performance

1. Introduction

Entrepreneurs can seek resources from a variety of different actors populating the entrepreneurial ecosystem from business angels to emerging startup accelerators. Some of these actors provide substantial financial support (Hellmann and Thiele 2015, Drover et al. 2017, Conti 2018), whereas others offer systematic mentorship and training to entrepreneurs (Hochberg 2016; Lyons and Zhang 2018; Assenova 2020, 2021). Likewise, seed investors may choose from a population of startups with different business ideas and diverse team compositions, each offering a different mix of skills and expertise. Establishing a successful relationship between a seed investor and a startup involves a bilateral decision-making process, in which both parties assess mutual fit. This mutual selection process underpins the formation of dyadic ties and is central to entrepreneurial success in resource-constrained settings.

The related literature on the topic mostly studies the value-adding effect of different seed investors in isolation, not considering the trade-offs between different options (Kerr et al. 2014a). The empirical literature on startup accelerators and incubators, for example, consistently identifies training and mentorship as the main channels through which accelerators add value, positively affecting startup performance (Assenova 2020, Hallen et al. 2020). It remains unclear, though, whether matching with these seed investors benefits every entrepreneur given the other available options. In this paper, we propose a theoretical framework and provide empirical evidence on how the complementarity or substitutability of resources between entrepreneurs and seed investors drives selection and value creation in the context of high-tech ventures (Cassiman and Valentini 2016, Mindruta et al. 2016, Fox et al. 2018, Chen et al. 2021).

In the modern entrepreneurial ecosystem, new ventures can raise funds from several different actors, including crowdfunding platforms, corporate venture capital (VC) programs, business angels, seed incubators, and accelerators. Broadly speaking, seed investors can be divided into two distinct categories based on the type of resources they provide. On one side, we have primarily financial investors, such as venture capitalists, crowdfunding platforms, and business angels, who mainly offer financial resources to entrepreneurs (Kerr et al. 2014a, Hellmann and Thiele 2015, Drover et al. 2017). On the other side, we find training institutions, such as accelerators or incubator programs (Cohen 2013, Assenova 2020). The attractiveness of this latter type of seed investor is more about their educational activities, such as mentorship and structured training programs, than the usually limited financial resources they offer. Whereas some financial investors may also offer valuable business advice to founders, this educational component is typically less systematic and organized compared with that of accelerators (Cohen 2013).

This study adopts a two-sided matching perspective, highlighting how the complementarity or substitutability of resources between the two sides shapes not only the matching process, but also the potential for subsequent value creation (Fox et al. 2018, Chen et al. 2021). More specifically, we argue that accelerator programs generate the most value for early stage entrepreneurs equipped with strong technological competencies but lacking in business knowledge. In these cases, accelerator training complements rather than substitutes the knowledge configuration of the startup team (Cassiman and Valentini 2016, Mindruta et al. 2016, Chen et al. 2021). Conversely, when entrepreneurial teams already possess solid business knowledge, both startups and investors may find that acceleration offers fewer benefits. In such cases, it is comparatively more convenient for these entrepreneurs to match with primarily financial investors, such as venture capitalists or business angels, as their existing expertise aligns with the investors' focus on scaling and expediting the go-to-market process (Hellmann and Thiele 2015).

We test our hypotheses using the Crunchbase (CB) database, focusing on a sample of startups that obtained at least one round of seed funding. We gathered data on the founding team's knowledge composition by combining information from both Crunchbase and LinkedIn. Our empirical analysis proceeds in two stages. In the first stage, we employ two-sided matching models (Mindruta et al. 2016, Fox 2018, Fox et al. 2018, Chen et al. 2021) to examine the sorting process between startups and seed investors. Consistent with our theory, we find that startups with strong technological competencies but lacking a business background are more likely to match with accelerators as their initial seed investor. In the second stage, we utilized a matched sample of startups with similar characteristics and identified complementarities from the two-sided matching analysis (Yu 2019, Conti and Graham 2020) to estimate the value-added effect of accelerators compared with primarily financial investors. Our findings show that accelerators have a strong value-adding effect in terms of subsequent funding collected only for startups whose team has a specialized technological background but lacks business knowledge. For other startups, accelerators have a negligible impact on performance. Moreover, we observe a clear substitution effect (Cassiman and Valentini 2016) of accelerator training for teams that include at least one member with a business background.

Our study contributes to the ongoing research on entrepreneurial strategies and their supporting institutions (Conti 2018, Yu 2019, Assenova 2020) from both theoretical and empirical standpoints. Theoretically, we propose a framework elucidating how knowledge complementarity or substitutability between entrepreneurs and seed investors drives selection and value creation in the context of high-tech ventures. By building on the concept of resource complementarity (Cassiman and Valentini 2016, Mindruta et al. 2016, Chen et al. 2021), we offer a more comprehensive framework for the sorting and value-creation process characterizing seed investments than the one offered by prior literature. This novel perspective helps reconcile contradictory findings in the startup accelerator literature regarding the effectiveness of these programs in promoting the success of early stage ventures (Smith and Hannigan 2014, Yu 2019, Hallen et al. 2020). Empirically, the adoption of a two-sided matching technique (Mindruta et al. 2016, Fox 2018) on a global sample of startups and seed investors allows us to quantify complementarities in a more precise way than prior literature. Whereas the quest to examine complementarities in strategy and entrepreneurship research is long-standing and several studies allude to their presence and importance, prior literature faces substantial methodological shortcomings that hinder its ability to advance this theory. Our theory and empirical analysis underscore the importance of mutual selection criteria between startups and seed investors.

2. Theoretical Background

Entrepreneurs facing resource constraints often seek help from external providers to bring their business ideas to market. Likewise, these providers evaluate entrepreneurs to determine which ventures align with their strategic goals and capabilities. A successful match emerges when there is a double coincidence of interests between seed investors and entrepreneurs. Understanding this mutual selection process requires examining the perspectives and priorities of both actors on either side of the market. In the sections that follow, we examine these perspectives in detail. In Online Appendix 1, we develop a very simple mathematical model formalizing our verbal arguments. The model is helpful to understand the necessary assumptions to derive our hypotheses.

2.1. On the Resource Needs of Early Stage Startups

From the perspective of early stage startups, two major resource needs stand out. The first and most fundamental need is financial resources, which are often scarce for new ventures. Financial resources can be sourced from a variety of public and private actors. On the public side, government or university programs provide subsidies and funds to promising startups (Wang et al. 2017, Conti 2018). On the private side, traditional seed investors of early stage startups are predominantly wealthy individuals, commonly known as angel investors, and venture capital firms (Hellmann and Thiele 2015). More recently, the ecosystem has expanded to include new actors, such as crowdfunding platforms, which leverage digital platforms to originate and pool funds (Mollick 2014). Despite the notable differences in their organization and behavior, all these actors share a common goal: providing financial support to early stage startups to speed up their growth and expedite their path to market. As their ultimate objective is to fund startups with high growth potential and secure substantial returns on their investments, these actors can be collectively categorized as primarily financial investors. Whereas some VCs and angel investors also offer mentorship, business advice, and strategic guidance, these efforts are typically informal and lack the structured and systematic approach needed to comprehensively address business entrepreneurial skill gaps. The primary focus of these investors remains on capital allocation.

However, whereas financial capital is critical, it is not the sole necessity during the initial stages of a venture. Business skills and acumen are equally vital for startup success (Bruhn et al. 2010). This includes capabilities such as business planning, marketing strategy, and broader managerial competencies. These skills enable entrepreneurs to refine their business models, identify growth opportunities, and navigate the complexities of scaling their ventures. In recent years, startup accelerators have emerged as significant players in the entrepreneurial ecosystem to offer such resources (Cohen 2013, Cohen et al. 2019b, Hallen et al. 2020). Unlike primarily financial investors, accelerators offer limited financial resources but distinguish themselves for their value-added services, such as mentorship and structured training programs (Cohen 2013). Their appeal to resource-constrained startups lies primarily in this emphasis on learning and knowledge acquisition, which sets accelerators apart in their role within the entrepreneurial ecosystem. Accelerators such as Techstars and Y Combinator have their own startup academies, in which early stage entrepreneurs receive mentorship and guidance to overcome critical challenges in launching and scaling their ventures. These programs feature a combination of seminars led by experienced mentors, personalized advice, and one-on-one mentoring sessions (Cohen 2013). The content of these sessions spans a broad spectrum of business and entrepreneurship topics, such as customer discovery, strategy testing, building the right team, developing a minimum viable product, and scaling operations (Miller et al. 2023, Santamaria et al. 2024). Similar to traditional educational institutions, accelerators also foster peer learning by supporting entrepreneurs in cohorts, enabling startup founders to exchange best practices and provide mutual support (Cohen et al. 2019a).

Several empirical studies identify education and mentorship as the most valuable contributions of accelerators. Qualitative field evidence indicates that these elements are often the primary motivations for ventures to join an accelerator program (Cohen 2013). Hallen et al. (2020) empirically demonstrate that learning is the main channel through which accelerators benefit startups. By employing a mixed-methods empirical approach on a sample of ventures that were accepted and almost accepted into top accelerators, they effectively ruled out alternative mechanisms such as signaling. This finding is corroborated by Gonzalez-Uribe and Leatherbee (2018), who investigate the impact of Start-Up Chile, an ecosystem accelerator, on new venture performance. Using a regression discontinuity design, their study revealed that the combination of training and mentoring with basic services such as funding and coworking spaces significantly enhances venture performance, whereas basic services alone do not. Further, the qualitative study of Cohen et al. (2019a) finds that startups participating in accelerators experience substantial changes in their business model, organization, and market strategy. These ventures often repositioned in the market, revised their target segments, adopted alternative technologies, explored new monetization strategies, and improved their communication with investors. Finally, Yu (2019) provides an interesting perspective on the impact of entrepreneurial education provided by accelerators. By analyzing a matched sample of startups, both participating in accelerators and not, she finds that the main benefit of accelerators is the speed at which the uncertainty around a startup business idea is resolved, helping entrepreneurs reject bad ideas early on.

Although empirical studies have consistently highlighted education and mentorship as the primary channels through which accelerators add value, there is mixed evidence regarding whether accelerator training systematically benefits all startups (Smith and Hannigan 2014), especially when compared with alternative options within the ecosystem, such as securing support from primarily financial investors. As detailed in the above paragraphs, the main difference between accelerators and primarily financial investors lies in the mix of resources each offers to early stage entrepreneurs. Accelerators focus on delivering substantial business education alongside limited financial resources, whereas primarily financial investors provide significant financial backing but minimal business training. We claim that support from accelerators is particularly valuable for teams that possess strong technical capabilities but lack business competence. This intuition is corroborated by qualitative research on startup accelerators. For instance, in the Hallen et al. (2020, p. 396) study of eight different accelerators, the founder of one accelerated startup stated, "We were certainly nerds that can code, but we didn't know a lot about product and customer development, and that [joining Accelerator K], was immensely helpful." Furthermore, Hallen et al. (2020, p. 396) also present qualitative evidence of a substitution effect between accelerator training and business knowledge. One accelerated startup quoted in their study suggested that accelerator training is mainly beneficial for people lacking a formal business education: "[Before Accelerator H], I didn't know what a business was or how to pitch something. I didn't know any of that stuff. I think if I had done an MBA I wouldn't have learned as much as I learned at (Accelerator H)" (Hallen et al. 2020). A few other studies offer preliminary evidence of this substitution effect. Lyons and Zhang (2018) find that, for people who already possess the resources and aptitude for entrepreneurship, entrepreneurship training programs akin to those provided by accelerators are less successful in guiding participants' career paths. Similarly, Assenova (2020) finds that incubator training and mentoring are more beneficial for entrepreneurs with limited business experience, suggesting that acceleration plays a crucial role in bridging the gaps in formal education and practical experience

2.2. How Do Investors Assess Founders' Human Capital?

Seed investments in early stage startups involve a high degree of uncertainty and financial risk. New ventures typically lack track records to demonstrate the viability of their business ideas or the ability of their founding teams to manage and scale their companies effectively. To mitigate this uncertainty, seed investors rely on a variety of signals when making investment decisions. Among these, the educational background, past work experience, and prior entrepreneurial track record of startup founders often play a pivotal role (Watson et al. 2003, Ko and McKelvie 2018). Although an extensive body of literature explores the importance of these factors in new venture financing (see Colombo 2021 for a review), we argue that the distinct logics underpinning investment decisions result in differing assessments of founders' human capital between primarily financial investors and accelerators. As far as primarily financial investors are concerned, the existence or lack of business competencies and managerial skills appear to be the major factors leading to accepting or rejecting an investment opportunity (Mason et al. 2017). In selecting investments, VCs see a competent management team as somewhat more important than the startup product or even the technology (Gompers et al. 2020). Founding teams with previous work experience in large companies (Esen et al. 2023) or MBAs from prestigious institutions (Bernstein et al. 2017) are significant signals that business angels and venture capitalists look for before investing in a startup.

Conversely, accelerators seem to discount teams' business competencies when evaluating a startup (Pierrakis and Owen 2022) in favor of technical ones. The study of two prominent accelerators by Smith and Hannigan (2014), for example, discovered that attendees are disproportionally more likely to have a computer science background from a prominent university than the overall entrepreneurship population. This behavior is motivated by the idea that accelerators can compensate for the lack of existing business skills in the startup team with their training. The story of Y Combinator, one of the first and most successful accelerators, exemplifies this strategy. Established in 2005 by Paul Graham and located in Silicon Valley, Y Combinator's original goal was to help technically skilled hackers from leading local universities start their digital businesses. In a 2007 blog post, Graham lamented that few smart hackers decided to start their own businesses and that those who did were rarely successful. The main reason for the low number of hackers among startup founders, he wrote, was a lack of business understanding, leading technologically competent people to focus on the wrong ideas and fail frequently: "Venture capitalists have a list of danger signs to watch out for. Near the top is the company run by techno-weenies who are obsessed with solving interesting technical problems, instead of making users happy" (Graham 2004). An accelerated training in business was, thus, necessary to help hackers overcome these biases and develop a viable business model. The success of this approach is demonstrated by the cases of Y Combinator's two most profitable investments, Airbnb and Dropbox. Two designers and one computer scientist founded Airbnb, whereas two computer scientists founded Dropbox. Nobody in either of the two startups had any prior business background. It's reasonable to assume that these companies would not have received funding from traditional venture capitalists or business angels.

2.3. Resource Complementarity, Matching, and Value Creation

Establishing a successful relationship between a seed investor and a startup involves a bilateral decision-making process. Our study emphasizes the critical role of resource complementarity in driving sorting and value creation in startup–seed investor matching. Specifically, the alignment between the resources possessed by startup teams and those offered by seed investors—whether accelerators or primarily financial investors—determines the value that can be created through their matching. This alignment reflects the perspectives, resources, and priorities of both parties in the matching process.

From the startup's perspective, founders seek resources that address their specific skill gaps and enable them to overcome key obstacles to growth. Startups with strong technological resources often lack the business expertise required to effectively commercialize their products and services. For these teams, accelerators offer structured mentorship and training programs that act as complementary resources, helping to fill critical knowledge gaps in areas such as customer discovery, business strategy, and scaling operations. From the seed investor's perspective, the decision to invest is shaped by its assessment of a startup's existing resources and the potential for its own intervention to create value. Accelerators, recognizing their strengths in providing business training, prioritize startups with substantial technological resources but limited business skills, as these teams stand to benefit the most from their intervention.

Conversely, when startups possess substantial business resources—such as prior business education or managerial skills—these same mentorship and training programs may be redundant. From the perspective of such startup teams, the overlap between their existing capabilities and the training provided by accelerators limits the incremental value of these programs. Similarly, financial investors, who focus on scaling resources rather than skill development, are more likely to prefer startups that already demonstrate strong business acumen as these teams are better positioned for rapid growth with financial backing.

Resource complementarity is a key concept in strategy literature, especially when value creation is determined by the joint effort of two or more partners (Makri et al. 2009, Cassiman and Valentini 2016, Mindruta et al. 2016, Chen et al. 2021). Complementarity arises when the incremental change in value creation resulting from one actor's attribute is augmented when the actor is cooperating with a partner having another attribute of interest. Empirical studies identify specific attributes that lead to complementarities in several contexts, including firm alliances/partnerships (Mindruta et al. 2016), university–industry collaborations (Banal-Estañol et al. 2018), CEO–firm matching (Chen et al. 2021), buyer–supplier relationships (Chatain and Mindruta 2017), venture capital investments in startups (Fox et al. 2018), and startup go-to-market strategy and organizational structure (Contigiani and Young-Hyman 2022). The importance of resource complementarity is amplified in competitive markets in which several actors compete for limited resources. In this situation, finding the most valuable partners is not the actors' profit-maximizing strategy; rather, they should look for partners who can generate the most incremental value using the other partner's unique resources (Fox et al. 2018).

Based on the previous theoretical arguments, we outline three main hypotheses to guide our empirical analysis. First, we predict positive assortative matching between startup teams and investors based on the complementarity/substitutability of their resources.

Hypothesis 1. *In a competitive matching market, there is positive assortative matching between entrepreneurial teams with specialized technology knowledge and accelerators. Conversely, there is negative assortative matching between entrepreneurial teams with business knowledge and accelerators.*

Second, we expect to observe greater (ex post) value generation in startup–investor pairs when resources are complementary. Both anecdotal evidence and primary data collected by the authors suggest that entrepreneurs and investors matching is far from being purely an optimization exercise.[1] As a result, we expect to find some observations in the sample in which considerations other than resource complementarity have prevailed in the match formation. We can use this source of variation to test whether actor pairings in line with Hypothesis 1 result in greater ex post value generation compared with mismatched pairings (Chen et al. 2021).

Hypothesis 2. *Startups with specialized technological knowledge generate greater value when paired with accelerators than when paired with primarily financial investors.*

Hypothesis 3. *Pairing with accelerators generates more value for startups without business knowledge than for those with business knowledge.*

3. Data

3.1. Seed Investors

The major source of data we used to test our propositions is the CB data set.[2] CB collects detailed information on recently founded startups, mostly in high-tech sectors, and their investors. It has rapidly become a point of reference for professionals seeking to invest in new ventures. This data source offers several advantages over more commonly used alternatives, such as VentureXpert, and it is increasingly used in academic research (Ter Wal et al. 2016, Lyons and Zhang 2018, Yu 2019, Roche et al. 2020). First, CB coverage is sufficiently exhaustive across major developed and emerging economies, and it has more early stage transaction data compared with other similar databases. Second, existing company accounts are generally not canceled, which reduces problems related to survival bias. Third, CB also contains granular information on the name, gender, job title, education, and employment history of large numbers of startup founders. Moreover, this information can be further complemented through public LinkedIn profiles, which are available for a significant number of founders.

From CB, we extracted all startups founded between January 1, 2004, and January 1, 2018.[3] Within this subset, we identified all ventures that received their first investment round from an accelerator. CB defines accelerators as investors who "provide a set amount of seed equity from a number of young startups in exchange for capital and mentorship. Accelerators will bring a cohort of startups in what is typically an on-site program which lasts for three to four months. At the end of the program, companies will 'graduate' from the program and may present their company in front of potential investors at the respective accelerator's Demo Day" (Crunchbase Knowledge Center). This sample represents our *Accelerator* group.[4] Following the same methodology, we selected an alternative group of startups that received their initial seed investment from a primarily financial seed investor such as a (micro)venture capitalist, business angel, government program, or crowdfunding platform. Because our research question focuses on early stage startups and investors, we limited our analysis to those startups that raised "preseed funding," defined as US$150,000 or less in the first funding round. This threshold was selected to roughly match the average amount of money invested by accelerators with that of other primarily financial early stage investors[5] and is consistent with prior literature. According to Hochberg (2016), accelerators' seed investment ranges from a few thousand dollars to US$150,000; this money is generally guaranteed upon acceptance into the program.[6] It is reasonable to assume that, below this threshold, primarily financial investors compete with accelerators in attracting the most promising ventures. It is also worth reporting that our results remain robust across different thresholds used to define preseed funding[7] as well as different sampling approaches. In Section 6, we explore an alternative sampling approach based on CB's classification of each startup's first funding round rather than using a fixed threshold. Both methodologies yield similar results. Table 1 reports the names of the 50 most important accelerators within our sample in terms of the number of funded startups. This list includes renowned organizations such as Y Combinator, Techstars, and 500 Startups. Moreover, many of these accelerators are featured in Jed Christiansen's list of prominent accelerators available at www.seed-db.com.

3.2. Startup Teams

To identify the founding members of the selected startups, we utilized information from the jobs and people tables, retrieved via the RESTful application programming interface (API) from the CB database. Specifically, we identified individuals affiliated with any of the selected startups (either currently or in the past) who reported their job titles as founder or cofounder. According to a recent benchmarking exercise, CB, along with Pitchbook, offers the best coverage regarding the number and educational backgrounds of founders among available data sets (Retterath and Braun 2020). The analysis indicates that CB reports 63% of all true founders as verified by funding contracts and original documentation.

To mitigate the issue of a missing founder or cofounder on CB, we expanded our search using LinkedIn. Specifically, for each startup in our sample, we collected the public profiles of all employees with a reported affiliation to that startup. Within this group, we identified as founders those individuals who, on their LinkedIn profiles, listed founder or cofounder as their job title. We employed two approaches for this purpose: either reviewing the social and professional networks often linked on CB profiles, specifically Facebook, Twitter, and LinkedIn, or for founders without a social media presence on CB, performing a manual Google search. Out of the 12,759 startups in the initial sample, our methodology helped in identifying the founders of 10,538 ventures. In total, we identified 22,994 distinct founders. It is noteworthy to mention that our success rate in identifying startup founders is 83%, a number similar to the one reported by Roche et al. (2020), who employed a methodology akin to ours, relying on CB and LinkedIn for founding team identification without using company websites or the Wayback Machine. In addition, the average number of founders per startup retrieved by our methodology is similar to that reported by Hallen et al. (2020), which is based on proprietary, highly confidential primary data provided directly by a set of accelerators. These comparisons serve as an important validation check.

For each startup founder, we classified the founder's educational attainment, coding as science, technology, engineering, and mathematics (STEM) any qualifications in one of three areas: (i) natural sciences, mathematics, and statistics; (ii) information and communication technologies; and (iii) engineering, manufacturing, and construction. Similarly, we coded as business any educational qualification belonging to the fields of business administration and law. Readers who are interested in the details of the classification method can consult the paper's online companion.

Recognizing that formal education represents only one component of an individual's knowledge base, we broadened our analysis to include alternative learning channels—which, though harder to observe, are crucial—such as specialized courses, on-the-job training, or self-study. For this reason, we complemented information about the educational background of founders with the self-reported skills on LinkedIn. These skills serve as reliable indicators of a founder's expertise domain. For instance, a founder reporting a skill such as "C, C++, Java, MySQL" likely has a technical background in computer science, whereas someone reporting skills such as "business development, business strategy, marketing strategy" has business expertise. As further explained in the online companion, we grouped founders' skills into 12 primary skill clusters: business, software, cybersecurity, creative arts, media, fashion,

Table 1. The Top 50 Accelerators in Our Sample

Name	No. of startups	Avg amount '000 USD	Country	Location	Foundation	Sector focused	In seed-db.com
Y Combinator	448	110.8	USA	Mountain View	2005	No	Yes
Start-Up Chile	402	40.2	CHL	Santiago	2010	No	No
Techstars	230	91.2	USA	Boulder	2006	No	Yes
Startupbootcamp	147	20.6	GBR	London	2010	No	Yes
500startups	138	108.7	USA	San Francisco	2010	No	Yes
Entrepreneurs Roundtable Accelerator	90	49	USA	New York	2011	No	Yes
AlphaLab	59	25	USA	Pittsburgh	2008	No	Yes
Eleven Startup Accelerator	54	41.1	BGR	Sofia	2013	No	Yes
Nxtp.labs	52	38.8	ARG	Buenos Aires	2011	Yes	Yes
MassChallenge	48	69.4	USA	Boston	2009	No	No
Bethnal Green Ventures	43	23.8	GBR	London	2012	Yes	Yes
Blueprint Health	42	20	USA	New York	2011	Yes	Yes
The Alchemist Accelerator	34	34.6	USA	San Francisco	2012	No	Yes
TLabs	31	30.3	IND	Noida	2011	Yes	Yes
Betaspring	30	42.9	USA	Providence	2009	Yes	Yes
Excelerate Labs	26	58.7	USA	Chicago	2010	No	Yes
GameFounders	25	19.2	MYS	Kuala Lumpur	2012	Yes	Yes
Propel Capital (Sting Accelerate) program)	25	35.1	SWE	Stockholm	2014	No	No
Lanzadera Accelerator	24	40.7	ESP	Valencia	2013	No	No
gener8tor	24	37.6	USA	Madison	2012	No	Yes
H2 Ventures (H2 Accelerator)	23	80.3	AUS	Sydney	2013	No	No
Capital Innovators	22	80.7	USA	St Louis	2011	No	Yes
DreamIT Ventures	22	29.1	USA	New York	2007	No	Yes
Plug and Play	22	46.2	USA	Sunnyvale	2006	No	No
TURN8 Seed Accelerator	21	40.7	ARE	Dubai	2013	No	No
Axel Springer Plug and Play	20	30.4	DEU	Berlin	2013	No	Yes
UpTech	20	28.2	USA	Covington	2012	Yes	Yes
Acceleprise	19	47.9	USA	Washington, DC	2012	Yes	Yes
Seedcamp (Became Seed Fund)	19	68.8	GBR	London	2007	No	Yes
Startup Wise Guys	19	27.5	EST	Tallinn	2012	Yes	Yes
Blue Startups	18	20.6	USA	Honolulu	2012	No	Yes
Slingshot Accelerator	18	26	AUS	Sydney	2013	No	No
StartupYard	18	23.2	CZE	Praha	2011	Yes	Yes
Entrepreneur First	17	47	GBR	London	2011	No	No
The Brandery	17	30	USA	Cincinnati	2010	No	Yes
Boomtown Accelerator	17	25	USA	Boulder	2013	No	No
Collider	16	78.4	GBR	London	2012	No	No
Emerge Venture Laboratory	16	41.8	GBR	London	2013	No	Yes
JumpStartFoundry	16	27.7	USA	Nashville	2010	Yes	Yes
CanopyBoulder	15	23	USA	Boulder	2014	No	No
FounderFuel	15	53.7	CAN	Montréal	2010	No	Yes
Portland Seed Fund	15	41	USA	Portland	2011	No	Yes
StartFast Venture Accelerator	15	26.8	USA	Syracuse	2011	Yes	Yes
SynBio axlr8r	15	82.7	IRL	Cork	2014	Yes	Yes
AngelPad	14	65.1	USA	San Francisco	2010	No	Yes
Flashstarts	14	34.9	USA	Cleveland	2013	Yes	Yes
Launchpad Accelerator	14	50	USA	Mountain View	2015	Yes	No
Start-Up Brasil	14	88.9	BRA	São Paulo	2012	No	No
Triangle Startup Factory	14	56.4	USA	Durham	2012	No	Yes
Accelerator Centre	14	31.6	CAN	Waterloo	2006	No	No

Notes. For the sake of comparison with seed-db.com, the table considers only investors that are consistently labeled as accelerators in Crunchbase (versions 2017 and 2020). The majority of them (70%) are present on the data set Seed-DB. Seed-DB is a platform created by Jed Christiansen, collecting data on 192 accelerator programs worldwide (https://www.seed-db.com/accelerators, last consulted on April 26, 2021). Startup incubators, as defined by Crunchbase, are not included in the list. Note that, for comparison purposes, the table aggregates the local branches of some accelerators (e.g. Techstars New York and Techstars Seattle) under the name of the main headquarters. To compute covariates, however, we relied on the locations of accelerators and startups as recorded in Crunchbase. In cases in which accelerators operate through multiple branches, Crunchbase typically specifies the location of the particular branch that facilitated the startup's acceleration. For instance, our sample includes 19 distinct locations for Techstars, illustrating the diverse geographic reach of its programs.

engineering, finance, communication, law, environment, and life sciences. Skills within the software, engineering, life sciences, and cybersecurity clusters were categorized under technology skills. Similarly, skills falling into business, finance, and law clusters were labeled as business skills. Finally, we classified founders based on their specialization in either technology skills or business skills. To accomplish this, we calculated a relative specialization index for each founder, allowing for a quantitative assessment of their main areas of expertise based on the previously outlined skill classifications. The index is defined as follows:

$$\textit{Specialization Index}_{i,j} = \frac{\frac{n_{i,j}}{\sum_j n_{i,j}}}{\frac{\sum_i n_{i,j}}{\sum_i \sum_j n_{i,j}}},$$

where $n_{i,j}$ represents the number of skills in founder i's resume classified in field j (with $j = Technology$, *Business*, *other*). The specialization index takes values greater than one for founder i when the share of the founder's skills in field j is greater than the share that this field has in the overall population of founders.

Leveraging LinkedIn data, we developed two distinct classifications for founding teams based on their knowledge base. The first relies solely on educational background, whereas the second incorporates both education and self-reported skills. Each strategy presents its unique advantages and limitations. Self-reported skills broaden the scope to include competencies acquired through job experiences though this approach might also lead to greater variability and possible inaccuracies. On the other hand, educational data are generally more reliable but fail to capture the diverse avenues through which individuals may acquire business or technological knowledge. For the education-based classification, we categorized ventures as pure tech companies (*Pure tech education*) if founders had only STEM degrees or a combination of STEM and nonbusiness degrees. Ventures with at least one founder possessing a business background were classified as *Business education* companies. Note that this latter category includes teams with only business, business and STEM, and business and other degrees. In our second classification, which integrates self-reported skills, a startup was classified as *Pure tech skill* if at least one founder holds a STEM degree or specializes in technology skills, provided that no founder possesses a business education or specialization in business skills. Conversely, a startup was classified as *Business skill* when any founder possessed business education or specialized in business skills. This skill-based approach resulted in a higher proportion of companies being classified as business startups, indicating that founders with technical or other nonbusiness education often gain business expertise through their past work experience.

Note that, in this paper, we decided not to use the job titles of our entrepreneurs in classifying their skills. This is due to the challenge of giving job titles a technology or business label. Whereas categorizing people's education (or self-reported skills) as either technological or business is comparatively uncontroversial, it is far more challenging to do so for job titles without making many arbitrary and simplistic assumptions. Most of the existing categorizations, even the recent ones based on generative artificial intelligence, tend to be more focused on identifying the hierarchical level of job titles rather than their business/technological nature (Albert et al. 2024). Furthermore, the relevant job title information for us should already be embodied in the self-reported skill variable that we created using LinkedIn data.

Beyond the main variables described above, we collected additional information on important startup characteristics. We recorded the venture's age at its first funding round (*Venture age*) and the amount raised in that initial deal (*Amount first round*). Additionally, we computed the number of founders (*Team size*) and their average age at the time of the company's establishment (*Team age*). The gender composition of the founding team was measured through a variable representing the share of female founders (*Share females*). Combining data from CB and LinkedIn, we captured startups' human capital using three binary variables. These variables identify if a venture includes at least one founder holding a PhD (*PHD*), a master's in business administration (*MBA*), or a master of science (*MSC*). Moreover, we introduced a dummy variable to identify ventures started by founders with academic experience (*Academic founder*) or those who graduated from top universities (*Top university*). For *Academic founder*, we checked if any founder had university employment—such as professor, research assistant, lecturer, or postdoc—before starting the venture. The prestige of universities from which founders received their degrees was assessed using the QS World University Rankings (2012), assigning *Top university* a value of one if a founder's degree came from a top 100 university as per QS rankings and zero otherwise. Furthermore, we coded each founder's history to determine if the founder founded other startups before initiating the current venture. Based on this, we generated a binary variable to identify if the founding team included at least one *Serial founder*, defined as a founder with experience launching a startup prior to the current enterprise. To account for the diverse ways founders can gain skills and knowledge of how to manage a startup, we followed Hallen et al. (2020) and introduced two variables: *Work experience* and *Top employer*. *Work experience* reflects the founders' professional experience, determined by computing the average number of years elapsed from receiving their degree (excluding MBA, which is typically attained after entry into the labor market) to the founding of the startup. *Top* *employer* is defined as a dummy variable that is assigned a value of one if any founder previously worked for one of the top 100 most common prior employers of startup founders in our data set. We used industry category tags provided by CB to classify our startups' activity sectors. Because companies can simultaneously have multiple tags, we performed a latent class analysis to assign each startup to a unique sector. Finally, we relied on CB data to identify the geographical location of our companies. As the startups in the sample are scattered across large numbers of countries, we grouped them into 11 broader geographical areas characterized by relative economic and cultural homogeneity. For the United States, we grouped startups at the state level. The online companion contains more information about how industries and regions are categorized.

3.3. Final Sample

Our final sample comprises 6,824 ventures, 61.8% of which (4,222) are accelerated ventures. Table 2 reports the descriptive statistics for the full sample of companies, selected through the process outlined in the preceding sections. For each variable coded in the study, we report both the mean and standard deviation, distinguishing between startups that received their initial funding round from an accelerator and those financed initially by a primarily financial investor. A detailed breakdown of the geographical location of our startups and their seed investors is provided in Online Appendix 2. A significant portion of startups in our sample are concentrated in specific regions: 43.0% are based in the United States, and 19.5% are located in Western Europe.

In general, accelerated startups differ in many important characteristics from other startups. Accelerated startups tend to have younger, less experienced but more diverse teams. Founders are more likely to come from top universities or top companies. Overall, the differences observed in the full sample reinforce the need to use a matching approach to identify the accelerator's causal effect.

It is important to note that our final sample represents only a subset of all accelerated companies in CB, excluding those for which CB did not report the first funding round amount or for which information on the founders' education was missing. In particular, the major drop in our sample occurs at the stage of detecting the educational background of our founders. Indeed, given our research question, we can include in our sample only the startups for which the education of all founders is available. Starting from an initial sample of 12,759 startups, we identified the founders of 10,538 ventures. Among these, we were able to collect educational information for the full team only in 6,824 of them (65%). Nevertheless, a comparison between the excluded and included companies displays no significant differences between the two groups. In Table 3, we compare the group of companies for which we have no information on the educational background with our sample to check for potential selection biases. Overall, the two samples look remarkably similar. The first group comprises ventures with a slightly larger number of founders and a slightly lower incidence of female founders. The remaining differences should not affect our findings in a significant way. The presence of a substantial selection bias in our final sample is, thus, very unlikely.

In the paper's online companion, we provide an additional validation exercise, triangulating CB data with data coming directly from top accelerators' websites. The results of this validation exercise demonstrate that Crunchbase may serve as a reliable information source regarding the coverage of accelerated startups. Of the 1,747 startups listed on Y Combinator's official website

Table 2. Initial Sample Descriptive Statistics

	Accelerator		Primarily financial investor			
Variable	Mean	Standard deviation	Mean	Standard deviation	Mean difference	p-value
Pure tech education	0.382	0.486	0.334	0.472	0.048	0.001
Business education	0.450	0.498	0.468	0.499	−0.018	0.142
Pure tech skill	0.305	0.461	0.255	0.436	0.05	0.000
Business skill	0.608	0.488	0.648	0.478	−0.04	0.001
Venture age	4.181	3.770	4.550	4.395	−0.369	0.002
Team age	31.366	6.071	33.569	7.889	−2.203	0.000
Team size	2.124	1.063	1.894	1.016	0.23	0.000
Female incidence	0.161	0.311	0.130	0.285	0.031	0.000
Serial founder	0.596	0.491	0.547	0.498	0.049	0.000
Academic founder	0.187	0.390	0.152	0.359	0.035	0.000
MSC	0.478	0.500	0.452	0.498	0.026	0.033
PhD	0.148	0.355	0.160	0.367	−0.012	0.156
MBA	0.191	0.393	0.195	0.396	−0.004	0.642
Work experience	6.671	5.992	8.213	7.029	−1.542	0.000
Top university	0.243	0.429	0.185	0.388	0.058	0.000
Top employer	0.223	0.416	0.153	0.360	0.07	0.000
Amount first round (log)	10.597	0.826	10.929	0.819	−0.332	0.000
Amount first round ('000s USD)	54.457	40.980	71.250	41.381	−16.793	0.000

Table 3. Checking for Selection Bias in Our Sample

	Educational background of all founders	
Variable	Not available	Available
Amount first round (USD)	64,422	60,860
Number of funding rounds	2.21	2.27
Venture age at the time of first round	4.35	4.32
Founding year	2013.2	2013.3
Team size	2.52	2.03
Female incidence	0.113	0.149
Three most represented sectors (%)	Commerce (25)	Commerce (29)
	Software (19)	Software (22)
	Media (12)	Media (12)
Three most represented countries (%)	United States (38)	United States (43)
	United Kingdom (8)	United Kingdom (8)
	India (3)	Spain (4)
Observations	3,714	6,824

and the 1,580 from Techstars, more than 96% were found in Crunchbase. Furthermore, for 86% of the startups associated with Y Combinator and 92% of those with Techstars, Crunchbase effectively identifies not only the companies' existence, but also their specific affiliations with these accelerators.

3.4. Empirical Design

Our empirical analysis follows a two-stage approach. First, we exploit a large sample of startups and information on the educational background and skills of their founders as a proxy for their knowledge resources (i.e., business versus technological) to study the sorting of startups and seed investors. To this end, we used a two-sided matching model (Mindruta et al. 2016, Fox 2018) to uncover the complementarities in value creation by looking at the sorting patterns of startups and seed investors. Second, we used a carefully selected matched sample (Yu 2019, Conti and Graham 2020) to provide an empirical estimate of the (ex post) value-adding effects of different seed investors when paired with different startups.

4. Expected Joint Value and Sorting

4.1. Two-Sided Matching Model

To provide evidence of our core proposition and Hypothesis 1, we adopted the two-sided matching model approach and maximum score estimator (MSE) pioneered by Jeremy Fox (Fox 2018, Fox et al. 2018) in the economics literature and Denisa Mindruta (Mindruta et al. 2016, Chen et al. 2021) in strategy. The philosophy of this approach is to embrace the endogeneity of partner selection and explicitly model it as a multisided, multidimensional, rational sorting process. The methodology is ideal for discovering assortative matching based on complementarities between partners' attributes (Chen et al. 2021). The chief advantage of maximum score estimation lies in its ability to yield consistent estimates even when researchers do not have data about one-sided unobserved attributes.

The approach relies on a few core assumptions. The first assumption is that agents choose their partners based on attributes that contribute to their payoff function. These attributes can be observable or unobservable to the researcher and matter jointly for value creation. The second and most important assumption is that sorting is a rational process in which agents, given their attributes, maximize their payoff function by identifying the best possible match among the available options. This process leads to a market-level equilibrium in which the value generated by any potential pairing of unmatched agents is less than (or equal to) the payoffs received by agents in their actual match (Mindruta et al. 2016, Chen et al. 2021). In other words, in the market equilibrium, it is impossible to generate more value by switching partners. The MSE exploits this condition between the value created by observed matches and counterfactual pairings to identify the joint value creation function and estimate the relative importance of different attributes in driving match formation.[8] We refer readers to Fox (2018) for a full technical discussion of the methodology and Mindruta et al. (2016) for a detailed discussion of its advantages over alternative methodologies that are commonly used in the literature.

The MSE approach requires us to define the matching markets, that is, the relevant markets in which startups compete for investors' attention and investors vie for the best investment deal. Following established literature (Mindruta et al. 2016), we employ the most conservative definition of matching markets based on investment year. Thus, seed investors are assumed to focus their search only on the set of startups that raised funding in the same year as the startups they actually end up matching with in the data set. It is worth reporting that our results are similar if we define matching markets based on a combination of sector and year (Fox et al. 2018, Chen et al. 2021).

Adopting the definition of matching markets based on year, we have a total of 15 different matching markets and 1,967,502 observations (potential startup–investor pairs). Observations include counterfactual pairings between startup and investor (each startup is paired with every seed investor that has made a first-round investment in the same year) as well as actual matches. Our model is a many-to-one matching model. Each startup appears once in the data, namely, in the year corresponding to the first funding year. On the other hand, an investor can appear multiple times if the investor has made multiple investments in the same year. In other words, an investor is treated as a single agent whose maximum number of matches is equal to the number of investments observed. Moreover, an investor can be also observed in multiple years.[9]

The peculiarity of the MSE method is that it estimates only bilateral preferences and not independent, one-sided characteristics of the agents. Thus, variables that we can include in the model as predictors of the two-sided matching must all come from interactions between attributes of startups and seed investors. The advantage of this approach is that fixed unobservable characteristics on just one side of the market (e.g., startup quality) do not introduce a bias to our estimates. This stems from the structure of the underlying mathematical model, wherein the effect of one-sided characteristics cancels out in the local maximization condition and inequalities required for pairwise stability.

Building on established literature, we know that one of the most important variables driving deal formation is the geographical location of agents (Hellmann and Puri 2000, Sorenson and Stuart 2001). Thus, we constructed a dummy variable, *Same country*, indicating whether the startup and the seed investor are located in the same country. For the U.S. startups, we instead created the dummy variable *Same U.S. state*, indicating whether the startup and the seed investor are located in the same U.S. state. We then quantified the distance between them using the mean standardized variable *Geographical distance*.[10] The variable *Tech similarity* measures the technological proximity between the investor and the startup. To construct this variable, we computed the number of past deals in which a given seed investor made a first-round investment in the focal startup's sector. Therefore, this variable captures the cumulative experience of the seed investor in the startup's sector, which is an important determinant of VC investments (Hsu and Kaplan 2004, Sørensen 2007). Given that this variable might exhibit a trend over time, we normalized it so that, for each year and sector, the variable ranges between zero and one with one being the investor with the most experience in that year and sector and zero being the investor with the least experience (Fox et al. 2018). In addition, we included the interaction between *Venture age* and *Average funding* disbursed by the investor to capture any sorting process related to venture stage: mature firms might select investors that provide more funding and vice versa. Again, we normalized *Average funding* to be between zero and one for each year. The interaction between *Top university* and *Accelerator* captures any potential positive correlation in sorting between entrepreneurs from prominent universities and accelerators (Smith and Hannigan 2014). The interaction between *Top employer* and *Accelerator* does the same using prominent companies and accelerators. Finally, *Accelerator* × *Pure tech education*, *Accelerator* × *Business education*, *Accelerator* × *Pure tech skill*, and *Accelerator* × *Business skill* represent our variables of interest to test Hypothesis 1. Descriptive statistics of the dyadic variables used in the matching model as well as startup characteristics are reported in Table 4.

4.2. Hypothesis 1 Results

Table 5 reports the coefficients estimated with the maximum score estimator using the educational background of founders, whereas Table 6 reports the same coefficients using the combination of founder's education and skill.[11]

Table 4. Descriptive Statistics for the Two-Sided Matching Model

Matching markets dyadic variables	Observations	Mean	Standard deviation	Minimum	Maximum
Same U.S. state	1,967,502	0.035	0.183	0	1
Same country	1,967,502	0.189	0.391	0	1
Geographical distance (std)	1,967,502	0.000	1.000	−1.514	2.961
Venture age × *Avg. funding*	1,967,502	0.000	0.001	0	0.081
Tech similarity	1,967,502	0.024	0.092	0	1
Top employer × *Accelerator*	1,967,502	0.082	0.274	0	1
Top university × *Accelerator*	1,967,502	0.093	0.290	0	1
Pure tech education × *Accelerator*	1,967,502	0.153	0.360	0	1
Business education × *Accelerator*	1,967,502	0.192	0.394	0	1
Pure tech skill × *Accelerator*	1,967,502	0.109	0.312	0	1
Business skill × *Accelerator*	1,967,502	0.282	0.450	0	1
Matching	1,967,502	0.003	0.057	0	1

Notes. The descriptive statistics of the matching markets refer to a novel data set constructed to run the two-sided matching model. In this data set, observations include counterfactual pairings between startup and investor (each startup is paired with every seed investor that has made a first-round investment in that year) as well as actual matches.

Table 5. Maximum Score Estimator Results Using Founders' Education

		95% confidence interval			
Variable	Coefficient	Symmetric		Asymmetric	
Same U.S. state	1				
Same country	7.1346	4.2657	10.0035	5.0326	10.3895
Geographical distance (std)	−0.5297	−0.7921	−0.2674	−0.8097	−0.4068
Venture age × *Avg. funding*	0.0043	−0.0001	0.0088	−0.0013	0.0073
Tech similarity	4.3587	2.8904	5.8270	3.4443	6.1587
Top employer × *Accelerator*	−0.0001	−0.0162	0.0160	−0.0256	0.0116
Top university × *Accelerator*	0.0379	−0.0051	0.0810	−0.0239	0.0670
Pure tech education × *Accelerator*	0.0467	0.0085	0.0849	0.0174	0.0893
Total inequalities	366,738				
Satisfied inequalities	353,028				

		95% confidence interval			
Variable	Coefficient	Symmetric		Asymmetric	
Same U.S. state	1				
Same country	8.2907	4.8998	11.6815	7.3104	12.5304
Geographical distance (std)	−0.4945	−0.7300	−0.2590	−0.7420	−0.3682
Venture age × *Avg. funding*	0.0057	0.0008	0.0107	−0.0021	0.0104
Tech similarity	4.7736	2.9400	6.6073	3.8878	6.8480
Top employer × *Accelerator*	−0.0001	−0.0147	0.0146	−0.0147	0.0214
Top university × *Accelerator*	0.0144	−0.0282	0.0572	−0.0475	0.0242
Business education × *Accelerator*	−0.0001	−0.0066	0.0066	−0.0191	0.0021
Total inequalities	366,738				
Satisfied inequalities	353,016				

Notes. Matching markets defined based on funding round year. For the choice of control parameters, we follow the advice in Storn and Price (1997), setting initial population number (100), crossover probability (0.5) and weighting factor (0.8), and maximum iterations (200). Boundaries are between −10 and 10.

For scale normalization, we set the coefficient for *Same U.S. state* to equal one. We compared the magnitude of other coefficients to this baseline. This is consistent with existing literature on the importance of geographical proximity in seed investing activities (Hellmann and Puri 2000, Sorenson and Stuart 2001). The magnitude of the coefficients represents the effect of one standard deviation change in the covariate on the expected joint value. Thus, a positive coefficient suggests that two variables are complements in value creation, whereas a negative coefficient suggests that two variables are substitutes.

The results of the maximum score estimator provides mixed support to our core proposition and Hypothesis 1. The complementarity between *Pure tech education/Pure tech skill* and *Accelerator* underpins positive assortative matching. This relationship appears strong and statistically significant. However, the substitution effect between *Business education/Business skill* and *Accelerator* is weak and poorly significant. The signs of the other variables are in line with our expectations too. *Geographical distance* displays a negative effect in driving expected value and, thus, match formation. On the contrary, *Tech similarity* between startups and investors has a positive effect. The positive coefficient of *Venture age* × *Average funding* suggests that mature startups seek investors that can provide more financial resources. The coefficients of *Top university* × *Accelerator* and *Top employer* × *Accelerator* are rarely statistically different from zero. In terms of coefficient magnitude, technological and physical distances seem to be the most important drivers of joint value creation and, thus, match formation. Whereas largely consistent with our theoretical framework, the results of the maximum score estimator indicate that an entrepreneur's educational background and skills (*Pure tech* or *Business*) are only a secondary driver of match formation. Our model shows a good fit with the data, satisfying roughly 96% of the total inequalities.

5. Ex Post Value Creation Analysis

In our second analysis, we aim to empirically estimate the value-adding effect on startups of different seed investors based on the ex post evaluation rather than ex ante sorting patterns. The goal of this analysis is to test Hypotheses 2 and 3. Building on the established literature in entrepreneurship finance (e.g., Gompers 1995), we capture startup value by looking at the amount of funding raised. Consequently, we measure investor value added using the incremental funding (in U.S. dollars) raised by the company in all funding rounds (*Incremental funding amount*), excluding the one provided by the focal investor (first round). We take the logarithm of this variable to reduce the influence of outliers and to simplify the interpretation of coefficients.[12] The total incremental funding serves as an effective indicator of

Table 6. Maximum Score Estimator Results Using Founders' Skills

		95% confidence interval			
		Symmetric		Asymmetric	
Variable	Coefficient				
Same U.S. state	1				
Same country	4.9423	1.4619	8.4228	0.9050	7.1946
Geographical distance (std)	−0.3673	−0.5681	−0.1664	−0.5681	−0.1462
Venture age × *Avg. funding*	0.0033	−0.0030	0.0096	−0.0040	0.0055
Tech similarity	4.5082	2.8912	6.1253	3.8490	6.3488
Top employer × *Accelerator*	−0.0001	−0.0210	0.0208	−0.0217	0.0097
Top university × *Accelerator*	0.0286	−0.0778	0.1351	−0.0899	0.0572
Pure tech skill × *Accelerator*	0.5017	0.0376	0.9656	0.5298	0.9669
Total inequalities	366,738				
Satisfied inequalities	353,093				

		95% confidence interval			
		Symmetric		Asymmetric	
Variable	Coefficient				
Same U.S. state	1				
Same country	6.3254	3.5265	9.1243	3.3322	8.3351
Geographical distance (std)	−0.3233	−0.6736	0.0269	−0.3867	0.0480
Venture age × *Avg. funding*	0.0038	−0.0042	0.0118	−0.0052	0.0052
Tech similarity	4.1539	2.7753	5.5325	3.0233	5.5855
Top employer × *Accelerator*	0.0010	−0.0193	0.0215	−0.0173	0.0307
Top university × *Accelerator*	0.0353	−0.0503	0.1210	−0.0701	0.0491
Business skill × *Accelerator*	−0.0005	−0.0578	0.0588	−0.0769	−0.0021
Total inequalities	366,738				
Satisfied inequalities	353,030				

Notes. Matching markets defined based on funding round year. For the choice of control parameters, we follow the advice in Storn and Price (1997), setting initial population number (100), crossover probability (0.5) and weighting factor (0.8), and maximum iterations (200). Boundaries are between −10 and 10.

a startup's overall value, offering advantages over narrower metrics such as the value of the subsequent funding round. This preference stems from the fact that the amount raised in the second round can heavily depend on the terms set during the first round of investment. As a matter of fact, it is a common practice among both accelerators and seed investors to use staged financing strategies, according to which each tranche of funding is contingent upon the startup reaching certain milestones, that is, points at which information is revealed about the quality of the project (Kerr et al. 2014b).

As an alternative measure, we use a discrete variable capturing whether the company collected enough funding to be in the top 50%, 25%, or 10% of the distribution in terms of total funding (*Top 50%*, *Top 25%*, *Top 10%*). We estimated linear regression models (ordinary least squares) for both dependent variables to simplify the interpretation of coefficients. Results of the limited dependent variable regressions are similar to a Logit or Probit specification. It is worth noting that our empirical design is unaffected by survival bias because our sample still contains failed companies.

In Section 6, we replicate our results using other dependent variables, including the total number of funding rounds, total number of employees, total revenue, and the likelihood of achieving a successful exit. The main limitation of this supplementary analysis is that this information is not available for all the startups in our matched sample.

5.1. Propensity Score Matching

The inherent limitation of an ex post analysis is the endogeneity associated with partner selection. To mitigate this issue, we carried out our analysis on a carefully selected subsample of startups that share similar characteristics, aiming to reduce any omitted variable concern. Following the approach of Chen et al. (2021) and Ozmel et al. (2020), we selected this subsample using propensity score matching (PSM) based on the identified complementarities from the two-sided matching analysis. Specifically, we used a Probit model to estimate the probability that a given startup matches with an accelerator as a seed investor based on the complementarities identified by the two-sided matching analysis as well as relevant startup characteristics. In the second stage, we only used observations with similar estimated probabilities. The key identification assumption of this approach is that selection into an accelerator for this subset of startups is the outcome of an almost random process (or a process driven by reasons exogenous to the key variables under study). Table 7 reports the descriptive statistics for the sample of companies resulting from the PSM matching. In the last columns of the table, we report the mean difference for

Table 7. Matched Sample Descriptive Statistics

	Accelerator		Primarily financial investor			
Variable	Mean	Standard deviation	Mean	Standard deviation	Mean difference	*p*-value
Pure tech education	0.368	0.482	0.325	0.469	0.042	0.013
Business education	0.446	0.497	0.491	0.500	−0.044	0.013
Pure tech skill	0.309	0.462	0.247	0.431	0.062	0.000
Business skill	0.602	0.490	0.661	0.473	−0.058	0.000
Venture age	4.319	3.783	4.343	4.198	−0.027	0.849
Team age	32.694	6.800	32.456	6.691	0.230	0.330
Team size	1.999	0.990	2.007	1.052	−0.007	0.831
Female incidence	0.149	0.306	0.146	0.297	0.002	0.826
Serial founder	0.549	0.498	0.567	0.496	−0.017	0.325
Academic founder	0.162	0.368	0.166	0.373	−0.004	0.732
MSC	0.452	0.498	0.457	0.498	−0.005	0.771
PhD	0.168	0.374	0.172	0.378	−0.004	0.736
MBA	0.203	0.402	0.189	0.392	0.013	0.338
Work experience	7.681	6.249	7.429	6.327	0.252	0.267
Top university	0.210	0.408	0.210	0.408	0.000	0.999
Top employer	0.185	0.389	0.172	0.377	0.013	0.321
Geographical distance (std)	−1.327	0.257	−1.319	0.262	0.007	0.527
Tech similarity	0.176	0.281	0.172	0.280	0.003	0.751
Expected joint value[a]	3.429	3.542	3.378	3.360	0.050	0.755
Amount first round (log)	10.481	0.876	10.911	0.832	−0.430	0.000
Amount first round ('000s USD)	50.648	41.072	70.493	41.239	−19.845	0.000
Observations	1,526		1,526			

[a]Estimated using Model 1 in Table 5. Results are qualitatively similar using Model 1 in Table 6.

each variable and the related *p*-value. Table 8 reports the distribution of startups by first round investor type,[13] whereas Tables 9 and 10 report, respectively, the sector and geographical distribution of ventures, separately for the *Accelerator* and *Primarily financial investor* groups. Table 11 reports the geographical distribution of U.S. startups only.

The PSM matching produced subsamples of very similar startups. We observe no substantial differences in terms of *Founding team size*, *Team*, or *Venture age*, educational attainment (*MSC*, *PHD*, *MBA*, and *Academic founder*), past entrepreneurial experience (*Self-employee founder* and *Serial founder*), years of work experience (*Work experience*), or gender composition (*Share females*). The two groups have the same share of founders who graduated from a top university (*Top university*) or worked for a prominent company (*Top employer*). There is a slightly larger share of *Pure tech skill* ventures and *Pure tech education* ventures in the *Accelerator* group. As the knowledge endowment of the startup is not directly

Table 8. Distribution of Startups by First-Round Investor, Matched Sample

Investor type	Accelerator	Primarily financial investor
Accelerator	1	—
Venture capital	—	0.36
Business angel	—	0.32
Micro venture capital	—	0.11
Government office	—	0.07
Funding platform	—	0.04
Angel group	—	0.04
University program	—	0.02
Corporate venture capital		0.01
Other	—	0.03
Total	1	1

Notes. The table reports the distribution of all startups in the matched sample by type of investor in the first funding round, separately for the two groups. *Other* includes private equity firms, family firm offices, investment banks, fund of funds, technology transfer offices, and nonequity funding.

Table 9. Distribution of Startups by Sector of Activity, Matched Sample

Sector	Accelerator	Primarily financial investor
Commerce	0.31	0.31
Software	0.22	0.22
Media & entertainment	0.11	0.11
Hardware	0.07	0.07
Mobile apps	0.05	0.05
Data analytics	0.05	0.05
Fintech	0.05	0.05
Biotech	0.04	0.04
Sales & marketing	0.03	0.03
Green tech & energy	0.03	0.03
Internet services	0.03	0.02
Design & fashion	0.01	0.02
Total	1	1

Notes. Sectors of activity are based on the industry tags reported in the CB database. See the online companion for a discussion of the methodology adopted.

Table 10. Distribution of Startups by Location, Matched Sample

Broad geographical area	Accelerator	Primarily financial investor
Africa/Middle East	0.02	0.02
Asia	0.03	0.04
Australia and New Zealand	0.02	0.02
Canada	0.02	0.02
Eastern Europe	0.05	0.05
United Kingdom	0.11	0.11
India	0.03	0.03
Israel	0.01	0.01
South America	0.03	0.03
United States	0.39	0.38
Western (Continental) Europe	0.29	0.29
Total	1	1

included among the propensity score matching variables, this small imbalance is consistent with our theoretical framework and the results of the two sided-matching model: accelerators attract more tech startups and slightly fewer business startups. Finally, the two groups do not differ in terms of the *Expected joint value* calculated using the two-side matching model results in Table 5. The key sources of matching value—*Geographical distance* and *Technological similarity*—have comparable values between the two groups too.

The two groups, however, differ slightly in the average amount of funding received in the first round: the *Accelerator* group received US$50,648, whereas the other group received US$70,393. Consistent with our theoretical framework, ventures going through an acceleration program generally receive a smaller amount of financing compared with startups selected by angel investors or other primarily financial seed investors. As we detail in the theory section, this does not necessarily reflect a different unobservable quality between the two types of startups. Rather, it is a consequence of how the intervention of accelerators is designed, that is, access to training and mentorship in exchange for a smaller amount of financial support. Looking at Tables 9–11, we can see that our samples are quite balanced in terms of sectorial and geographical distribution of startups.

5.2. Hypotheses 2 and 3 Results

We first investigate the interaction between *Pure tech* and *Accelerator* on the incremental funding amount collected by the startup. Table 12 reports our main results in the matched sample using *Pure tech education*, whereas Table 13 reports the same results using *Pure tech skill*. We represent graphically the results of Table 13, Model 1, in Figure 1.

In general, *Pure tech* startups raise less funding than other startups, but the coefficient is weakly significant. The *Accelerator* baseline coefficient is negative or not statistically significant, depending on the model

Table 11. Distribution of U.S. Startups by State, Matched Sample

US state	Accelerator	Primarily financial investor
AL	0.3	0.2
AR	0.5	0.5
AZ	1.0	0.5
CA	31.8	33.5
CO	3.2	2.5
CT	0.5	0.5
DC	1.5	1.9
DE	0.2	0.0
FL	1.9	1.7
GA	1.5	1.3
IA	0.2	0.3
IL	4.2	3.4
IN	1.0	1.2
KY	1.0	1.0
MA	5.9	5.2
MD	2.2	2.5
MI	0.8	1.0
MN	0.7	0.5
MO	0.8	1.2
MT	0.3	0.2
NC	1.2	1.3
NE	0.5	0.3
NH	0.2	0.2
NJ	0.3	0.8
NM	0.2	0.2
NV	0.2	0.0
NY	13.1	11.8
OH	3.9	4.5
OR	0.8	0.5
PA	5.9	6.9
SC	0.2	0.2
TN	2.7	3.0
TX	6.1	5.6
UT	0.7	1.0
VA	1.0	1.5
WA	2.7	2.5
WI	1.2	0.5
Total	100	100

specification. However, the interaction term between *Pure tech* and *Accelerator* reveals a positive coefficient that is both statistically significant and economically large. According to Model 1, Table 12, *Pure tech education* startups that join an accelerator raise 37% more subsequent funding than similar startups that engaged with primarily financial investors. Similarly, Model 1 in Table 13 indicates that *Pure tech skill* startups that participate in an accelerator program benefit from a 28% increase in subsequent funding compared with similar startups that engaged with primarily financial investors. Results are similar if we use dichotomous dependent variables. Figure 1 visually illustrates our findings, showing that accelerators have a positive and sizable effect on subsequent funding only for *Pure tech* ventures. Overall, these results offer robust support to Hypothesis 2.

In the next tables, we test whether accelerator programs complement or substitute the business knowledge owned by the entrepreneurial team. Thus, we use

Table 12. Impact of Accelerators on Pure Tech Education Ventures, Matched Sample

	Incremental funding (1)	Top 50% total funding (2)	Top 25% total funding (3)	Top 10% total funding (4)
Accelerator	0.027	−0.061	−0.054	0.000
	(0.757)	(0.007)	(0.006)	(0.977)
Pure tech education	−0.086	−0.039	−0.033	−0.015
	(0.421)	(0.157)	(0.174)	(0.343)
Accelerator × *Pure tech education*	0.376	0.072	0.078	0.027
	(0.012)	(0.059)	(0.019)	(0.225)
Constant	1.425	0.543	0.283	0.098
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,052	3,052	3,052	3,052
R^2	0.004	0.003	0.002	0.000

Notes. The dependent variable in column (1) is the log of funding amount. *p*-values in parentheses.

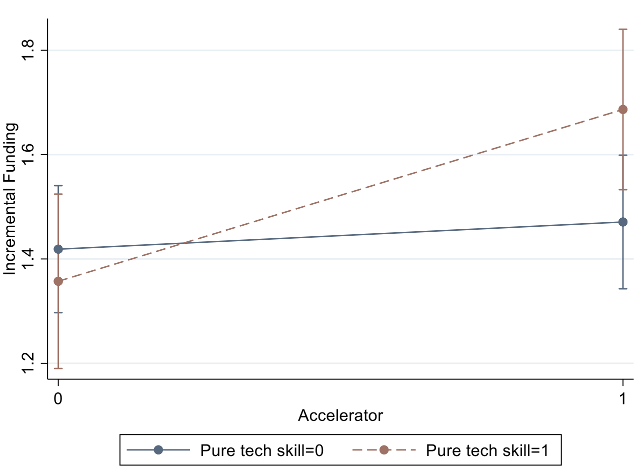
Table 13. Impact of Accelerators on Pure Tech Skill Ventures, Matched Sample

	Incremental funding (1)	Top 50% total funding (2)	Top 25% total funding (3)	Top 10% total funding (4)
Accelerator	0.041	−0.070	−0.050	0.010
	(0.667)	(0.004)	(0.018)	(0.507)
Pure tech skill	−0.018	−0.024	−0.014	0.000
	(0.864)	(0.362)	(0.540)	(0.983)
Accelerator × *Pure tech skill*	0.257	0.074	0.052	0.000
	(0.073)	(0.042)	(0.102)	(0.982)
Constant	1.405	0.540	0.278	0.093
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,052	3,052	3,052	3,052
R^2	0.003	0.002	0.002	0.001

Notes. The dependent variable in column (1) is the log of funding amount. *p*-values in parentheses.

the variable *Business* as the main independent variable. The baseline group consists of ventures with teams lacking any business background. Our main results are reported in Tables 14 and 15. Results in Table 14 rely on *Business education* to classify founders' knowledge base, whereas Table 15 uses *Business skill*. We represent graphically the results of Table 15, Model 1, in Figure 2.

Figure 1. (Color online) Accelerator Effect on Pure Tech Skill Startups



Notes. Estimates are based on Table 13, Model 1. Bars represent 95% confidence intervals.

The baseline *Accelerator* effect is generally positive. However, looking at the interaction, we see a consistent and strong substitution effect between *Accelerator* and having a person with a business education or skill. In general, these findings suggest that, whereas selecting an accelerator can have a positive effect on the total value of the average startup, the effect becomes indistinguishable from zero with *Business* startups. In Model 1 of Table 14, for example, we estimate a positive *Accelerator* coefficient of 0.287 ($p = 0.003$) and a negative interaction coefficient of −0.244 ($p = 0.086$). Thus, a startup with *Business education* joining an accelerator raises roughly the same amount of subsequent funding as a similar startup that engaged with primarily financial investors. It is interesting to note that having a founder with business knowledge on the team increases startup value as indicated by the positive coefficient of *Business education.* In line with our theory, this effect is more pronounced when the startup matches with a primarily financial investor as opposed to an accelerator. Results are similar but less significant when using *Business skill* in Table 15. The *Accelerator* coefficient is 0.289 ($p = 0.014$) and the interaction coefficient is −0.179 ($p = 0.225$). Looking at Figure 2, we can see the graphical representation of our results in Table 15. Accelerators tend to increase startup value. However, such an increase is smaller in the case of *Business skill* startups. In this latter

Table 14. Impact of Accelerators on Business Education Ventures, Matched Sample

	Incremental funding (1)	Top 50% total funding (2)	Top 25% total funding (3)	Top 10% total funding (4)
Accelerator	0.287	0.003	0.007	0.029
	(0.003)	(0.900)	(0.764)	(0.051)
Business education	0.358	0.110	0.090	0.051
	(0.000)	(0.000)	(0.000)	(0.001)
Accelerator × *Business education*	−0.244	−0.077	−0.064	−0.038
	(0.086)	(0.034)	(0.043)	(0.082)
Constant	1.222	0.476	0.228	0.068
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,052	3,052	3,052	3,052
R^2	0.006	0.008	0.007	0.004

Notes. The dependent variable in column (1) is the log of funding amount. *p*-values in parentheses.

Table 15. Impact of Accelerators on Business Skill Ventures, Matched Sample

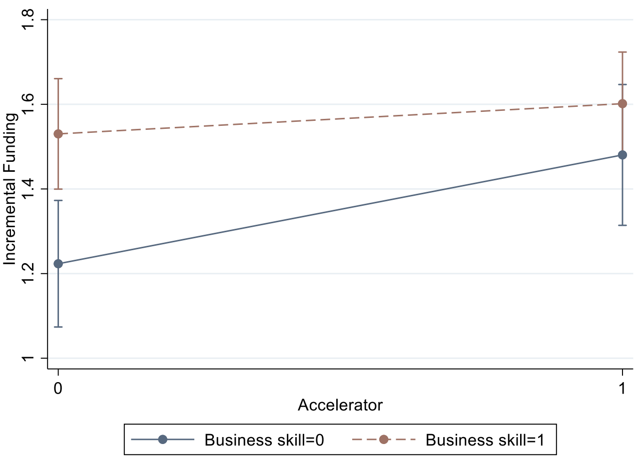
	Incremental funding (1)	Top 50% total funding (2)	Top 25% total funding (3)	Top 10% total funding (4)
Accelerator	0.289	0.008	0.007	0.026
	(0.014)	(0.778)	(0.785)	(0.136)
Business skill	0.328	0.114	0.081	0.041
	(0.002)	(0.000)	(0.001)	(0.010)
Accelerator × *Business skill*	−0.179	−0.063	−0.047	−0.024
	(0.225)	(0.095)	(0.149)	(0.291)
Constant	1.180	0.455	0.219	0.066
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,052	3,052	3,052	3,052
R^2	0.006	0.008	0.005	0.003

Notes. The dependent variable in column (1) is the log of funding amount. *p*-values in parentheses.

case, accelerators have a negligible effect. These results provide support to Hypothesis 3.

In conclusion, our hypotheses are strongly supported by the combined results of our regressions. In particular, *Pure tech* startups benefit greatly from the training provided by accelerators. However, when the entrepreneurial team already has enough business knowledge, such training is redundant and only slightly useful. When paired with investors who are primarily financial, startups with business teams produce more value.

Figure 2. (Color online) Accelerator Effect on Business Skill Startups



Notes. Estimates are based on Table 15, Model 1. Bars represent 95% confidence intervals.

6. Additional Analyses

In this section, we further test the robustness of our main analysis. We replicate our results using (i) an alternative way to select our sample, (ii) an alternative way to select our control group of primarily financial investors, (iii) an alternative classification of accelerators cross-checked with a different data set, (iv) different dependent variables, (v) including serial entrepreneurship as a source of business knowledge, and (vi) focusing only on the most influential accelerators. Furthermore, we study how (vii) *Pure business* and *Mixed tech-business* backgrounds, the remaining knowledge configurations of startup teams, interact with the *Accelerator* effect. Finally, to corroborate our findings and provide additional evidence of the theoretical mechanism, (viii) we performed an additional analysis using primary data gathered through an anonymous survey. For the sake of simplicity, all the analyses presented in this section use the startup team's educational background as a primary independent variable. Results are similar when we use skills instead of education. All the tables are available in Online Appendices 3 and 4.

6.1. Alternative Sample Selection Based on CB Funding Classification

In our main analysis, we limited our sample to those investors that provided US$150,000 or less in the first funding round. This threshold was selected to roughly match the average amount of money invested by accelerators with that of other primarily financial early stage investors. In Online Appendix 3, Tables A3.1 and A3.2, we replicate our analysis with an alternative sample selected based on the funding type classified by CB and no threshold. Specifically, we included in the control group all startups that raised a first round of funding in the form of a preseed, grant, angel, crowdfunding, or convertible note[14] from a nonaccelerator. The downside of this approach is the large variation in the first-round funding between startups as the CB funding type classification is not very precise.[15] To mitigate this problem, we trimmed the top 10% of the funding distribution (more than US$1,300,000). Even with this correction, the first round of funding provided by primarily financial investors is substantially larger than the one provided by accelerators with a difference of more than US$100,000. Nevertheless, the core results of the paper remain unchanged. According to our estimates, *Pure tech education* startups that join an accelerator raise 54% (p = 0.002) more subsequent funding than similar startups that engaged with primarily financial investors. Conversely, *Business education* startups that join an accelerator raise 40% (p = 0.019) less subsequent funding than similar startups that engage with primarily financial investors.

6.2. Alternative Control Group of Primarily Financial Investors

In our main analysis, we use a heterogeneous group of primarily financial investors ranging from crowdfunding platforms to government programs. In Online Appendix 3, Table A3.3, we replicate our analysis using venture capitalists and business angels as our only primarily financial investors. Results are similar, except the *Accelerator* × *Pure tech* coefficient is larger, and the *Accelerator* × *Business* coefficient is smaller and weakly significant. We estimate that *Pure tech education* startups that join an accelerator raise 46% (p = 0.011) more subsequent funding than similar startups that engage with primarily financial investors. Conversely, *Business education* startups that join an accelerator raise 15% (p = 0.388) less subsequent funding than similar startups that engage with primarily financial investors.

6.3. Alternative Accelerator Classification

In our main analysis, we rely on the classification of accelerators provided by CB. As an additional robustness check, we cross-checked CB information with Pitchbook data to develop a more accurate classification. Specifically, we created the variable *AcceleratorPB* with value one if the given seed investor is classified as an accelerator by both CB and Pitchbook. Seed investors with contrasting classification were removed from the sample. The results, reported in Online Appendix 3, Table A3.4, are consistent with our main analysis.

6.4. Alternative Performance Variables

We combined CB with Pitchbook to access additional startup performance variables. In Online Appendix 3, Table A3.5, we replicate our analysis using the *total number of funding rounds*, *total number of employees*, *total revenue*, *successful exit*, and *failure* as alternative dependent variables. The variable *successful exit* in particular is coded as one in case the startup was acquired by another larger company or went public and zero otherwise. The main limitation of this supplementary analysis is that such information is not available for all the startups in our matched sample. Thus, we need to limit our analysis to a subsample of startups with good coverage between the two data sets. In general, coefficient signs are consistent with our framework. However, results are statistically weak in the case of *total revenue* and insignificant with *successful exit* or *failed*. According to our estimates, *Pure tech education* startups that joined an accelerator received 0.3 more funding rounds (p = 0.013), hired five more employees (p = 0.000), and generated 70% more revenue (p = 0.145) than similar startups that engaged with primarily financial investors. However, acceleration has no effect on the likelihood of survival.[16] Conversely, *Business education* startups that joined an accelerator received 0.23 fewer funding rounds (p = 0.036) and hired 20 fewer employees (p = 0.000). Acceleration did not impact the revenue, likelihood of successful exit, or likelihood of failure of these entrepreneurs.

6.5. Prior Entrepreneurship Experience as Source of Business Knowledge

In our main analysis, we define the variable *Business* based on the educational background or, alternatively, the skills of the entrepreneurial team. As an additional robustness check, we defined business knowledge in a broader way, including teams with at least one serial entrepreneur. This new variable is named *Business&Serial*. The results, reported in Online Appendix 3, Table A3.6, are consistent with our main analysis. Serial entrepreneurs or entrepreneurs with a business education that joined an accelerator raise 32% (p = 0.048) less subsequent funding than similar startups that engage with primarily financial investors.

6.6. Most Influential Accelerators

We replicated the analysis focusing only on the most influential accelerators. We built the syndication network, in which a pair of investors is linked by a tie if they coinvested in the same venture, and computed the eigenvector centrality index (Bonacich 1987) to identify the most influential accelerators. For this robustness check, we restricted our analysis to the startups that participated in the top 50 accelerators based on their eigenvector centrality scores. Note that this variable is positively correlated with accelerator's portfolio size. Results are reported in Online Appendix 3, Table A3.7. Interestingly, as we restrict the sample to only the most influential accelerators, the baseline *Accelerator* coefficient becomes larger and the interaction effects weaker. These findings suggest that startups can benefit from influential accelerators through channels other than training and knowledge acquisition. Additional benefits include reputation or access to an extensive network of investors.

6.7. Pure Business and Mixed Tech-Business

In Online Appendix 3, Table A3.8, we show the *Accelerator* effect on *Pure business* and *Mixed tech-business* ventures.[17] The results in the table are in line with our theoretical framework. The interaction coefficient for *Pure business education* is large and negative, -0.42 with $p = 0.026$, suggesting that teams with only businesspeople benefit substantially less than other teams from accelerator programs. The *Mixed tech-business education* baseline coefficient is large and positive, 0.52 with $p = 0.000$, suggesting that this is the best knowledge configuration for startup teams independent of seed investor. This result confirms the tacit assumption of our theoretical model that both technological and business knowledge are required to launch a successful high-tech startup, and these skills are complementary. Interestingly, the interaction between *Mixed tech-business education* and *Accelerator* is not statistically different from zero (0.03 with $p = 0.824$). Also, in this case, the finding is consistent with our theoretical framework. Accelerators' value-added effect on *Mixed tech-business* is larger than on *Pure business.* However, accelerators' value-added effect on *Mixed tech-business* is smaller than on *Pure tech.* These two effects compensate each other and result in a null net effect of accelerators on *Mixed tech-business.*

6.8. Evidence from Primary Data

In Online Appendix 4, we describe our survey, primary data analysis, and main results. The survey was developed using Qualtrics, directed to all companies in our data set, distributed via email, contained 12 questions in total, and took no more than three minutes to complete. Our final sample contained 236 unique responses, 56% of them from startups that are accelerated and 44% from startups that raised seed funding from primarily financial investors (control group). The survey responses are consistent with the theory outlined in this study. Entrepreneurs recognize that accelerators provide more value-adding activities than primarily financial seed investors such as VCs or business angels. Specifically, accelerators offer more valuable feedback on the business model, idea, customer development, and pitching. Overall, as hypothesized, they provide superior training on business-related issues and mentoring. Conversely, VCs and business angels contribute with more financial resources. The picture becomes more interesting when we break down the impact of accelerator value-adding activities based on team educational background. As expected, *Pure tech* entrepreneurs report a stronger positive impact of the acceleration program on their startup. Specifically, they report a stronger accelerator impact in the areas training on business issues, pitching the idea, and networking with mentors. Conversely, *Business* entrepreneurs report a smaller accelerator impact in these areas.

7. Conclusion and Discussion

In this study, we propose a theoretical framework for how resource complementarity or substitutability (Cassiman and Valentini 2016, Mindruta et al. 2016, Fox 2018) between entrepreneurs and seed investors drive selection and value creation in the context of high-tech ventures (Conti 2018, Yu 2019, Assenova 2020). Specifically, we show how accelerators act as providers of complementary knowledge to specialized tech entrepreneurs who lack the necessary business knowledge to launch a company. Conversely, the value-adding effect of accelerators is negligible in the case of entrepreneurial teams already possessing these resources in the form of business education or skills. Our theoretical framework is supported by the observed sorting of startups and seed investors as well as the ex post analysis of the value generated by different startup–seed investor pairings. This study contributes to the literature on the drivers of entrepreneurial performance (Assenova 2020, Hallen et al. 2020), highlighting the strategic role played by seed investors as providers of heterogeneous resources (Kerr et al. 2014a, Hellmann and Thiele 2015, Conti 2018, Conti and Graham 2020). From a methodological perspective, the adoption of a two-sided matching technique (Mindruta et al. 2016, Fox 2018, Chen et al. 2021) in the context of startups and seed investors helps us to quantify complementarities in a more precise way than what prior literature achieves. In addition, controlling for startup–investor expected joint value as well as precisely matching accelerated startups with similar counterparts that raised funding from primarily financial investors helps to reduce endogeneity concerns in the subsequent ex post value creation analysis.

The results of our empirical analysis offer practical implications for practitioners, startup founders, and investors. One aspect worth discussing is the difference in magnitude between the ex ante and ex post results on value creation. Our two-sided matching models reveal that knowledge endowment of a startup team (tech versus business) is only a secondary driver of match formation. The primary drivers remain geographical proximity and technological preferences of the investor. This is quite surprising considering that we observe a substantial increase in startup ex post value when the resources of the two actors are complementary and not substitutive. According to our estimates, specialized tech teams can raise up to 40% additional funding when they are supported by an accelerator, whereas business teams do not display any significant benefit. We believe the main reason for this discrepancy is incomplete information in the matching market. As a result, sorting between startups and seed investors is not a completely rational process, but there is still a sizable amount of value dissipated by inefficient allocation of resources. The diffusion and adoption of the theoretical framework outlined in this paper has, thus, the potential to substantially improve the decision making of startups and investors with positive effects on both sides.

It is important to acknowledge the main boundary conditions of this study, which offer opportunities for future research. As we detailed in the additional analyses section, our theoretical framework holds when we compare an average accelerator with an average primarily financial investor. As we restrict the sample to only the most influential accelerators (but keep the quality of primarily financial investors constant), the baseline accelerator effect becomes larger and the interaction effects weaker. These findings suggest that startups can benefit from influential accelerators through channels other than basic business training. For these reasons, our theoretical framework is less likely to hold in this context. These results are consistent with Hallen et al. (2020), who find a strong positive effect of top accelerators on startup performance, independent of teams' educational background, but no effect for less popular ones. Another important boundary condition is that our results relate to a carefully selected subsample of high-tech startups that reached a minimum quality threshold to raise some funding (and, thus, be considered investment-worthy). Our results might not be generalizable to the overall startup population. Finally, our theoretical framework produces good results in anticipating the average effects, but it is weaker in predicting outliers such as extreme values of the performance distribution or rare events such as successful startup exit through acquisition or IPO.

The paper also has several limitations, which are mostly related to data availability. For example, whereas our anonymous survey provides some qualitative evidence on the source of complementarity between accelerators and startups with specialized technological teams, we are unable to identify all the micromechanisms behind it. The substitution effect between accelerator intervention and business knowledge could be due to alternative explanations such as the resistance of people with a business background to adopt innovative or nontraditional approaches to startup launch that go against what they learned in school (Leatherbee and Katila 2020). Similarly, the complementarity between *Pure tech* teams and accelerator training could be driven by accelerators' focus on fast experimentation. Technical cofounders are able to carry out rapid prototyping quickly and efficiently because they have the technical skills to do so. We are unable to identify such micromechanisms with the current data, but these represent potentially interesting questions for future research. Finally, our operationalization of startup performance is far from perfect. Whereas it is common in the literature to use variables such as total funding to measure startup value (Gompers 1995), we do not have complete information about startup revenue or revenue growth, which might be better measures for startup success.

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Endnotes

[1] See Section 6, Additional Analyses, for more details on our primary analysis.

[2] Data have been obtained through the academic Crunchbase API, https://data.crunchbase.com/docs.

[3] The first known accelerator, Y Combinator, was launched in 2005 and was quickly followed by TechStars in 2006.

[4] CB classifies investors into 22 different types, for example, venture capital, corporate venture capital, funding platform, and so on. Our initial sample includes startups funded by investors classified in CB either as accelerators or as incubators because practitioners often use the two labels interchangeably. Moreover, because of the crowdsourced nature of CB, some investors that label themselves accelerators would be considered incubators by scholars, whereas others that refer to themselves as incubators would be labeled as accelerators (Cohen 2013).

[5] According to our raw data, accelerators disbursed on average approximately US$40,000 per startup from 2008 to 2013. After that year, however, the average amount of seed funding provided by accelerators increased considerably, reaching nearly US$90,000 in 2018.

[6] Techstars, for example, contributed US$20,000 as a stipend to support living expenses during the program in 2022 and, in return, received 6% equity in the company. 500 Startups' standard accelerator deal in 2022 was a US$150,000 investment in return for a 6% stake.

[7] Results are robust with US$50,000, US$100,000, and US$200,000 as thresholds.

[8] Identification of the maximum score estimator relies on inequality relations rather than equalities. Estimates are those parameter

values that, once plugged into the inequalities defining the equilibrium conditions, lead to the greatest number of them being satisfied.

[9] The same investor is treated as a different actor in each market.

[10] The variable is standardized by subtracting from it its sample mean and by dividing it by its standard deviation. Mean and standard deviations are calculated using the two-sided matching data set including the counterfactual pairings. Thus, the measure can be considered as the relative distance of the matched pairs compared with all the alternative ones.

[11] For the estimation, we implement an algorithm in R using the MSE-R code developed by Theodore Chronis, Christina Tatli, and Panaghis Mavrokefalos, in collaboration with Denisa Mindruta. The code is available at https://github.com/MaximumScoreEstimator/MSE-R. Their code builds upon the maximum score estimator for matching data developed by Jeremy Fox (2018).

[12] In this way, model coefficients approximate percentage changes.

[13] The inclusion of VCs in this group requires further clarifications. Whereas it is true that VCs generally invest in later rounds, this is not always the case and depends on the opportunities at hand. Many smaller VCs (or microVCs) are open to making a preseed investment in the right startup. This observation is consistent with recent literature. Hellmann et al. (2021) find that, contrary to popular opinion, angel financing and VC financing are substitutes rather than complements. Their evidence points to the existence of parallel streams of angel and venture capital funding with fewer transitions between streams than is traditionally assumed.

[14] This type of financing is very common among accelerators. Thus, we also included this investment type in the control group.

[15] Another limitation is that very large first round amounts are more likely classification mistakes in which CB misses the real first round investment received by the company and classifies the subsequent round as the first one. We identified a few of these classification mistakes in our comparison between CB and Pitchbook.

[16] Survival is often cited as a poor performance indicator in the case of high-growth startups. Paradoxically, low-growth startups tend to survive longer and have a lower probability of failure than high-growth startups (Arora and Nandkumar 2011).

[17] Ventures in which founders have only business degrees were labeled as pure business companies (*Pure business education*). Ventures with at least one team member with a business background and one team member with a STEM background were labeled as *Mixed tech-business* education.

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