KU LEUVEN

FACULTY OF ECONOMICS AND BUSINESS

Unlocking Startup Potential: Research, Signals, and Support Structures



Dissertation presented to obtain the degree of Doctor in Business Economics

by

Maud Thys

Number 947 2025

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Chapter 1

General Introduction

1.1 The Relevance of High-Potential Startups

High-growth potential new ventures play a critical role in driving innovation, economic renewal, and job creation, distinguishing themselves from the vast majority of startups that remain small or stagnant throughout their lifecycles. While most startups either fail or grow modestly, a small subset of firms contributes disproportionately to new employment and economic output, underlining the importance of understanding the distinct characteristics and developmental pathways of these exceptional companies (Acs and Mueller, 2007; Birch, 1979; Colombelli et al., 2016; Henrekson and Johansson, 2010; Söderblom et al., 2015). These firms are vital not only because they introduce novel products, technologies, and services to the market, but also because they act as engines of structural economic transformation by replacing outdated incumbents and stimulating competitive pressures within industries (Acs and Mueller, 2007; Henrekson and Johansson, 2010).

Given the rarity and strategic importance of high-growth ventures, scholars and policymakers have placed increasing emphasis on understanding what sets these firms apart from the vast majority of startups that fail to scale significantly (Barringer et al., 2005; Demir et al., 2017). A growing body of literature suggests that high-growth startups are shaped by a combination of distinct founder characteristics, firm-level attributes, business practices, and human resource management (HRM) strategies, which collectively allow these ventures to exploit market opportunities more effectively than their peers (Barringer et al., 2005). Specifically, Demir et al. (2017) propose five fundamental drivers of high growth: human capital, strategy, HRM, innovation, and organizational capabilities. These dimensions in-

teract in complex ways to determine a firm's ability to recognize and exploit growth opportunities, navigate uncertainty, and sustain competitive advantage.

Beyond these internal factors, recent research also highlights the importance of external drivers. Becker-Ritterspach et al. (2022) emphasize that high-growth firms rely not only on their internal resources and capabilities but also on external linkages, such as international market access, partnerships, and participation in innovation ecosystems. Similarly, Dörrenbächer et al. (2017) point to the significance of organizational identity and the ability to adapt context-specific processes as additional factors that shape firm growth trajectories. Together, these studies underscore that high-growth startups are not solely the result of superior internal processes but also of their capacity to leverage and integrate resources and knowledge from their broader environment.

While understanding these drivers is essential for explaining why some firms succeed in achieving high growth, it is equally important to identify which of these critical resources, capabilities, or strategic competencies are still lacking in potential high-growth startups. A firm may, for example, possess technological innovation but lack the market knowledge or strategic flexibility necessary for scaling, or it may have strong human capital without the dynamic capabilities to reconfigure its resources in response to changing market conditions (Demir et al., 2017). This awareness is vital for the design of targeted public policies and private interventions aimed at overcoming such gaps. As Demir et al. (2017) emphasize, growth-supporting mechanisms, whether in the form of public subsidies, incubators, or private-sector accelerators, must be carefully aligned with the specific growth barriers that firms face. When such interventions focus on building the missing elements, be it market access, managerial expertise, or strategic routines, they can substantially improve a firm's chances of realizing its high-growth potential.

Therefore, the study of high-growth firms requires not only an understanding of the factors that enable success but also a diagnostic perspective that reveals what is absent or underdeveloped in potential high-growth ventures. This dual focus is critical for designing both effective public policy and private-sector initiatives that are capable of nurturing the next generation of high-impact startups. As emphasized by Becker-Ritterspach et al. (2022), it is not only firm-internal capabilities that matter but also the surrounding institutional environment, including supportive funding schemes, regulatory conditions, and infrastructure, which plays a decisive role in sustaining and enabling firm growth. Without such an enabling context, even resourceful firms may struggle to transform their potential into realized high-growth

outcomes.

1.2 The Role of Venture Capital in High-Growth Startups

1.2.1 Enabling and signaling high-growth startups

Venture capital (VC) plays a critical role in the development of high-growth startups (Gompers and Lerner, 2001), as both an enabler of growth and a signal of potential to other market participants. On the one hand, venture capital provides substantial financial and non-financial resources that enable young firms, especially those with significant upfront investment needs and long payback periods, to scale, expand internationally, and further develop their technologies, thereby facilitating growth (Bertoni et al., 2011; Colombo et al., 2010; Gompers et al., 2020). On the other hand, the involvement of professional VC investors serves as a powerful market signal, including to customers, partners, and additional investors, that the startup possesses credible growth potential and quality (Colombo et al., 2010; Hsu, 2004; Lerner and Nanda, 2020; Svetek, 2022). This is because venture capitalists are known to engage in extensive screening, selection, and monitoring processes before committing their resources (Gompers et al., 2020; Kaplan and Strömberg, 2001, 2004). This signaling function plays a crucial role in reducing information asymmetries, which are inherent to early-stage, high-uncertainty environments (Colombo et al., 2010; Lerner, 1999; Spence, 1973).

The importance of VCs' role is particularly evident when considering the constraints faced by startups in their formative phases. These firms typically operate under severe uncertainty (McKelvie et al., 2011), liability of newness (Bruderl and Schussler, 1990; Stinchcombe, 1965), and persistent resource scarcity (Gupta et al., 2006; Lee and Lévesque, 2023). Among these constraints, limited access to financial capital critically affects their ability to invest in essential activities such as technology development, market entry, and organizational scaling (Colombo and Grilli, 2005; Lee and Lévesque, 2023). Bridging the so-called "valley of death", the phase where technical feasibility has been demonstrated but market readiness and financial backing remain insufficient, is widely acknowledged as a central challenge for deep-tech and high-growth startups (Gbadegeshin et al., 2022; Michelfelder et al., 2022; Savaneviciene et al., 2015).

Beyond the provision of capital, VC investors provide complementary resources crucial to startup growth. Independent VC firms supply not only large funding rounds but also strategic guidance, access to critical networks, and validation for subsequent financing rounds (Bertoni et al., 2011; Colombo et al., 2010). Corporate VCs contribute similarly, but additionally offer technological infrastructure, collaborative innovation structure, and pathways to market access unavailable to standalone firms (Shuwaikh and Dubocage, 2022; Wang et al., 2019). Business angels are particularly important at the earliest stages, providing not just capital but also hands-on mentorship and early market insights, helping to mitigate the pervasive information asymmetries young ventures face (Croce et al., 2018). Through these various contributions, venture investors help new firms overcome deficiencies in managerial capabilities, commercialization experience, and industry connections (Demir et al., 2017), all critical for setting a trajectory toward sustained, high-growth development.

Venture capital also performs an indispensable signaling role in startup ecosystems. Receiving VC funding, whether from independent firms, corporate investors, or angels, functions as a strong certification mechanism. It communicates to external stakeholders such as customers, alliance partners, and additional financiers that the startup has passed a stringent evaluation process and is considered a credible, growth-worthy entity (Davila et al., 2003; Kaplan and Strömberg, 2004; Kleinert et al., 2020; Svetek, 2022). Numerous studies affirm that VC-backed firms achieve superior post-investment outcomes in sales growth, employment generation, and market penetration compared to their non-VC-backed counterparts (e.g., Bertoni et al., 2011; Colombo and Grilli, 2005). This signaling effect is particularly valuable in high-uncertainty industries, such as deep-tech or science-based sectors, where the inherent complexity and unpredictability of technologies make it difficult for external observers to assess firm quality and potential (Colombo et al., 2007; Michelfelder et al., 2022).

Securing venture capital is therefore widely recognized as a significant milestone in a startup's development path, not only because of the capital infusion it provides, but also because of the reputational benefits and credibility signals it generates (e.g., Colombo et al., 2010; Davila et al., 2003; Kaplan and Strömberg, 2004; Kleinert et al., 2020; Svetek, 2022). Startups that succeed in attracting VC investment are often perceived as having validated business models, capable founding teams, and scalable technologies, which reduces uncertainty for other stakeholders such as corporate partners, potential customers, and later-stage investors (Colombo et al.,

2010; Gompers et al., 2020). This "stamp of approval" effect can make a decisive difference in market entry and expansion efforts.

However, despite its importance, only a small proportion of startups ever manage to secure venture capital funding. Estimates consistently suggest that less than 1% of new ventures receive formal VC backing (Gompers et al., 2020), a reflection of the stringent selection criteria and high-risk aversion among professional investors (Kaplan and Strömberg, 2001, 2004; Nunes et al., 2014). Many high-potential startups, despite promising technologies or ambitious visions, fail to attract VC due to a lack of key investment signals or struggle to overcome early-stage uncertainties. This rarity underscores the need for mechanisms that help startups enhance their visibility and appeal to venture capitalists.

1.2.2 Public and private interventions to boost VC involvement

In this regard, public policies and private interventions play an increasingly recognized role in improving startups' chances of attracting VC funding. Programs such as competitive accelerators can serve as important signals to investors by validating the startup's market potential, team quality, and development progress (e.g., Assenova and Amit, 2024; Cohen et al., 2019b; Venâncio and Jorge, 2022). Likewise, government R&D grants and subsidies can reduce perceived technological risks and signal external validation, thereby increasing the attractiveness of the startup to private investors (Islam et al., 2018; Kleer, 2010). Bianchi et al. (2019) highlight that such public funding mechanisms serve a dual purpose, not only supporting resource development but also enhancing the firm's visibility and credibility in the eyes of potential partners and venture capitalists.

The importance of these complementary mechanisms suggests that public and private signals, such as subsidies, grant awards, and accelerator certifications, should be considered integral to the startup funding ecosystem rather than substitutes for private capital. As noted by Lerner (2010), well-designed public interventions can address information asymmetries and early-stage financing gaps, effectively preparing startups for private venture capital markets. The combination of early validation through public or private third-party endorsements can help reduce investor skepticism, enabling a broader pool of startups to access the resources needed for scaling and internationalization (Colombo et al., 2010). In sum, the dual role of VC as an enabler and signal of startup quality underscores the significance of policies and

support mechanisms designed to increase startups' VC readiness. Without such targeted interventions, whether through selective funding schemes or endorsement mechanisms (e.g., accelerators), many potentially high-growth startups may remain unnoticed by venture capitalists, thereby limiting their growth trajectories despite inherent technological or market promise (Colombo et al., 2010; Lerner, 2010). This raises the importance of integrated policy approaches that align public support with private market mechanisms to foster the emergence of the next generation of high-growth firms.

1.3 Academic Startups as High-Potential New Ventures

1.3.1 Academic startups' challenge to attract VC funding

Academic startups are widely seen as ventures with exceptional, high-growth potential. Their access to advanced knowledge, technological sophistication, and highly trained human capital positions them as important vehicles for transferring scientific innovation into economic and societal value (Bonardo et al., 2011; Botelho et al., 2021; Shane, 2004; Tartari and Stern, 2021). These ventures also play a growing role in addressing 'grand societal challenges' (De Silva et al., 2021; Fini et al., 2018; George et al., 2016).

However, academic startups often face significant barriers in realizing their growth potential. They tend to be more complex and slower to mature than other high-growth ventures, while also operating under greater technological and market uncertainty (Fini et al., 2023; Pahnke et al., 2015). These challenges are compounded by investor concerns about founders' business acumen, commercial commitment, and the viability of their business models (Balven et al., 2018; Colombelli et al., 2016; Dörrenbächer et al., 2017; Fini et al., 2022; Gubitta et al., 2016; Mathisen and Rasmussen, 2019; Meyer, 2003; Rasmussen et al., 2011), all of which contribute to a financing gap during the early stages of development (Roche et al., 2020).

Venture capital (VC) plays a critical role in helping such startups grow. It not only provides the resources necessary for technology development, market entry, and organizational scaling, but also acts as a powerful signal of startup credibility and growth potential (Colombo et al., 2010; Spence, 1973). Yet, many academic startups

struggle to attract VC due to the high uncertainty they present, especially when technologies are scientifically validated but not yet market-proven (Gbadegeshin et al., 2022; Toole and Czarnitzki, 2007).

Public policy interventions can help bridge this gap. By offering grants and other support mechanisms, public programs can reduce early-stage resource constraints while simultaneously enhancing the perceived quality and legitimacy of startups in the eyes of investors (Berger and Hottenrott, 2021; Howell, 2017; Lerner, 1999; Söderblom et al., 2015; Zhao and Ziedonis, 2020). This signaling role of public support is particularly relevant for academic ventures, where technological and market uncertainty is high, with large ambiguity regarding organizational capabilities and goals.

This sets the stage for **Chapter 2**, which empirically investigates whether public support increases the likelihood that academic startups secure VC funding and whether this effect differs from that for non-academic startups. Drawing on signaling theory (Spence, 1973), we consider how public funding may operate differently as a signal for academic entrepreneurs, given their distinct characteristics. While public support is a well-known signal in startup financing (Berger and Hottenrott, 2021; Howell, 2017; Zhao and Ziedonis, 2020), its effectiveness for academic startups remains uncertain. It may be more valuable due to expert evaluations that reduce technological uncertainty (Lerner, 1999; Pahnke et al., 2015; Toole and Czarnitzki, 2007). However, investors might discount its relevance given academic founders' familiarity with grants (Colombo et al., 2016; Fini et al., 2022).

The paper draws on a rich longitudinal dataset from the IAB/ZEW Startup Panel in Germany, complemented with equity investment data. Germany offers a fertile empirical context due to its strong science base, robust public support programs, and growing policy emphasis on commercializing academic research (Lehmann et al., 2024). The study makes several contributions. First, it directly compares the effect of public support on VC financing across academic and non-academic startups. Second, it explores how the signal's strength varies across industries, such as high-tech manufacturing versus software and services, and across investor types, including business angels and institutional VCs. Third, it evaluates the timing of the effect, assessing whether public support acts as a short-term certification mechanism or has a lasting influence. By doing so, the study contributes to a broader understanding of how targeted public interventions can unlock the growth potential of academic startups. Highlighting the need to take into consideration the indirect benefits of governmental incentives when creating and evaluating these policies. It

provides practical insights for policymakers, universities, and investors seeking to foster science-based entrepreneurship and promote the successful commercialization of academic research.

1.3.2 Are all academic startups alike, and how does that translate into high-growth potential?

Although academic startups are often portrayed as inherently high-potential ventures, this assumption deserves greater scrutiny. In reality, academic startups appear to represent a heterogeneous group (Czarnitzki et al., 2014; Goel and Grimpe, 2012), and there might be substantial variation in how their scientific origins translate into commercial outcomes. Much of this ambiguity stems from inconsistencies in how academic startups are defined, ranging from strict interpretations focused on university spin-offs from patented research (e.g., Agarwal and Shah, 2014; Iacobucci et al., 2011; Link et al., 2015; Mathisen and Rasmussen, 2019; Shane, 2004) to broader notions that include ventures started by any academic personnel drawing on general scientific experience (e.g., Breschi et al., 2021; Coad et al., 2021; Colombo and Piva, 2008; Roche et al., 2020). These definitional differences carry important implications: they mask substantial variation in the resources, competencies, and strategic orientations these ventures possess, and therefore in their capacity to achieve high growth.

As discussed earlier in the context of high-potential startups, growth is not determined by a single factor but emerges from the presence and interaction of multiple internal drivers. Prior studies consistently highlight a range of critical enablers, including human capital, strategic vision, innovation capabilities, organizational routines, and resource alignment (Barringer et al., 2005; Covin et al., 2006; Demir et al., 2017). However, the absence or underdevelopment of any one of these can inhibit the realization of growth potential. For instance, strong technological knowledge may be insufficient if not paired with business development skills or if the startup lacks the strategic flexibility to respond to market feedback (Dörrenbächer et al., 2017).

Moreover, the growth potential of academic startups could be the result of a dynamic interplay between internal capabilities and their interaction with the external environment. As Becker-Ritterspach et al. (2022) argue, it is not only firm-internal resources that matter but also the broader institutional environment in which startups are embedded. In the case of academic startups, universities provide not only

cutting-edge scientific knowledge but also access to a broader innovative context, including networks, infrastructure, and knowledge spillovers, that can shape how internal resources are activated and translated into growth opportunities. This interplay might be especially relevant for opportunity recognition. Internal drivers, such as the founder's human capital, affect not just execution capacity but also the ability to perceive, evaluate, and act upon high-quality opportunities within or beyond the academic sphere (Davidsson and Honig, 2003; Marvel et al., 2020). For example, scientific expertise may support innovation-driven growth, but may also narrow the venture's focus, limiting adaptability (Nagle and Teodoridis, 2020). Conversely, startups led by academic entrepreneurs with broader managerial or industry experience (Goel and Grimpe, 2012; Mosey and Wright, 2007) may be better equipped to identify viable commercial paths, even if their technological edge is less pronounced. In short, high scores on one growth driver may not compensate for the absence of others, and different combinations of capabilities can lead to divergent growth outcomes.

Building on this logic, **Chapter 3** introduces a Human Capital (HC) perspective to empirically examine the heterogeneity among academic startups and how it relates to their innovation output and sales performance. To better understand the growth potential of academic startups, it is necessary to distinguish between divergent types of academic entrepreneurs and their implicit distinctive features. By introducing Human Capital Theory (Becker, 1964; Unger et al., 2011), we shift the focus from a traditional knowledge transfer perspective and bring the academic startups into a new theoretical perspective. Research-intensive ventures tend to excel in radical innovation due to deep technological expertise (Marvel and Lumpkin, 2007; Stephan, 2014), but often struggle with early commercialization because of limited market and managerial skills (Colombo and Piva, 2008; Gourville, 2005; Gubitta et al., 2016). Conversely, startups with lower research intensity often possess broader university-acquired human capital and industry experience, which enhances their ability to recognize innovative opportunities and generate early market traction (Goel and Grimpe, 2012; Nagle and Teodoridis, 2020; Wennberg et al., 2011).

Using longitudinal data from the IAB/ZEW Startup Panel, the paper develops a nuanced typology of academic startups, ranging from highly research-intensive ventures to those that draw more broadly on scientific human capital. It examines how these differences relate to innovation output and sales performance in the years following foundation. In doing so, the study moves beyond a simplistic view and categorization of academic startups and offers a more refined understanding

of which types of academic entrepreneurship are most likely to realize high-growth potential, and under what conditions. By demonstrating that varying degrees of research engagement are associated with distinct growth trajectories, we provide clarity to previously inconsistent findings and strengthen the empirical basis for tailored policy and support interventions. These insights are particularly relevant in the context of high-growth startup support. As academic startups continue to be seen as key drivers of innovation-led growth, understanding their diversity helps ensure that public and institutional resources are matched to their specific development pathways. Whether the goal is to support radical innovation or market-oriented expansion, recognizing the heterogeneity within academic entrepreneurship is vital for shaping more effective strategies to unlock their full potential.

1.4 Accelerated Startups as High-Potential New Ventures

Accelerators have become an integral feature of modern entrepreneurial ecosystems, particularly for identifying and nurturing high-potential startups. Much like venture capital (VC), accelerator programs serve a dual function: they provide early-stage ventures with critical resources, such as mentorship, training, networks, and seed funding, while also acting as powerful signals of startup quality to outside investors (Assenova and Amit, 2024; Cohen et al., 2019a; González-Uribe and Reyes, 2021; Kleinert et al., 2020). In fact, accelerators often precede VC investors in a startup's lifecycle, playing a formative role in preparing ventures for the rigorous demands of scaling and investment readiness.

From a high-growth entrepreneurship perspective, this early-stage intermediation is vital. Startups face considerable liabilities of newness, resource scarcity, and market uncertainty (Gupta et al., 2006; McKelvie et al., 2011; Stinchcombe, 1965). For many, the window between product feasibility and investment readiness, the so-called "valley of death", is especially difficult to cross without structured support (Everts and Drew, 2024; Gbadegeshin et al., 2022; Michelfelder et al., 2022; Savaneviciene et al., 2015). Accelerators attempt to close this gap. By selecting promising ventures and guiding them through structured development processes, accelerators aim to enhance a startup's growth potential and credibility, two factors critical for securing downstream VC financing (Beyhan and Fındık, 2022; González-Uribe and Reyes, 2021; Goswami et al., 2018; Hallen et al., 2020; Vandeweghe et al.,

2019; Venâncio and Jorge, 2022).

Real-world examples underscore this potential: successful startups like Dropbox, Airbnb, and 9GAG participated in accelerator programs such as Y Combinator, and subsequently raised substantial VC funding. Dropbox, for example, joined Y Combinator in 2007, where the founders received $15,000 in seed funding, mentoring (notably, advice to bring in a co-founder), and the chance to pitch at demo day. Shortly thereafter, Dropbox secured $1.2 million in VC funding from Sequoia Capital, a critical milestone that propelled the company toward unicorn status (Alford, 2018; Tracxn, 2025). Similarly, Airbnb entered Y Combinator in 2009 and received $20,000 along with intensive guidance, including advice to engage more directly with customers. This strategic shift, particularly through a hands-on push to expand operations in New York, played a pivotal role in the company's growth. Airbnb went on to raise $600,000 in seed funding from Sequoia Capital later that year (Knowledge at Wharton Staff, 2017; Malhotra, 2024). Finally, 9GAG, after participating in 500 Startups, and Y Combinator in 2012, saw rapid user growth, reportedly reaching 70 million unique visitors globally, and attracted $2.8 million in venture funding from Silicon Valley investors the same year (Grin, 2015; Y Combinator, 2025).

These cases illustrate how accelerators can serve not just as training grounds but as launchpads for some of the world's most successful ventures. Yet, despite the rapid growth in the number of accelerators globally (Drori and Wright, 2018), their outcomes remain highly uneven (Chan et al., 2020). Some programs consistently produce standout ventures, while others struggle to yield meaningful outcomes. Given the diversity in accelerator program designs, this variation raises an essential question: which elements of accelerator design are critical for enabling high-growth outcomes, such as attracting substantial post-acceleration equity investment?

This question becomes especially important when considering that early-stage VC financing is not only a growth enabler but also a strong external signal of venture quality (Colombo et al., 2010; Hsu, 2004; Lerner and Nanda, 2020; Svetek, 2022). As with VCs, accelerators themselves must be able to credibly select and prepare ventures, or their signaling function may falter. Prior literature emphasizes considerable variation in accelerator structures, content, and regional strategies (Bergman and McMullen, 2022; Hallen et al., 2020; Uhm et al., 2018). Yet there is limited consensus on which design features are most critical, particularly for ventures aiming to secure high levels of post-acceleration investment.

Chapter 4 addresses this gap by exploring which design elements are necessary, rather than just beneficial, for enabling startups to secure substantial equity

financing after acceleration. Using necessity-based logic, the study identifies program components without which high venture capital (VC) or business angel (BA) investment outcomes are unlikely to occur. This approach diverges from most existing studies that focus on average effects or additive sufficiency. Instead, it centers on identifying what is fundamentally required for startup growth, particularly through the lens of early-stage capital acquisition.

The analysis draws on rich global data from the Entrepreneurship Database Program at Emory University, backed by the Global Accelerator Learning Initiative (GALI). Covering accelerator programs in North America, Latin America, and South Asia, this study explores regional variations in design necessity and identifies key bottlenecks. Findings indicate that accelerator grants emerge as a necessary condition for high equity investment in several regions. Moreover, certain region-specific elements are necessary to access any equity funding at all, pointing to the importance of tailoring accelerator design to local ecosystems. By identifying what must be in place for high levels of early-stage investment to occur, this paper contributes a critical new perspective to the literature on accelerators and high-growth entrepreneurship. These findings sharpen our understanding of which program features are truly indispensable for enabling early-stage ventures to convert potential into performance. Just as earlier chapters emphasized the importance of venture capital and public support in shaping the trajectories of academic and science-based startups, this study highlights accelerator design as a key lever in fostering venture growth. By applying necessity logic, the analysis moves beyond additive assumptions and instead focuses on threshold conditions, those elements without which high levels of post-program investment cannot be achieved, regardless of other strengths. In doing so, it provides a valuable lens for understanding how to support startups in progressing from potential to tangible growth opportunities, offering theoretical, methodological, and practical insights for scholars, policymakers, and ecosystem builders working to cultivate the next generation of high-impact firms.

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Chapter 2

Public Support and VC Financing in Academic Startups[1]

We investigate public support and venture capital (VC) investment in academic startups. Government support may enable follow-on investment by providing a quality signal to investors. This signal is especially important for academic startups, which face large funding gaps due to their complexity, cutting-edge nature, and uncertainty regarding the founders' management capabilities and commitment. Using a panel of startups in Germany, our analyses confirm that academic startups are more likely to obtain follow-on VC investment after receiving public support than non-academic startups. Further, this effect is limited in time, lasts longer for academic startups, is concentrated in high-tech manufacturing firms, and is stronger for investments from business angels. Our findings have implications for policymakers seeking to foster academic entrepreneurship through policy programs and VC investment.

[1]Co-authors: Maikel Pellens (KU Leuven, ZEW), Hanna Hottenrott (ZEW, TUM), & Marius Berger (ZEW). This is a preprint version of the manuscript accepted for publication in the Strategic Entrepreneurship Journal (SEJ). Please note that this version may differ from the final published article in terms of copyediting, formatting, and minor revisions. The definitive version will be available via the Strategic Entrepreneurship Journal at http://doi.org/10.1002/sej.70003

2.1 INTRODUCTION

Academic startups are important conduits for disseminating scientific knowledge to business practice (Botelho et al., 2021; Shane, 2004). They are often based on cutting-edge scientific knowledge, with high technological potential (Bonardo et al., 2011; Gubitta et al., 2016; Tartari and Stern, 2021). Academic entrepreneurs are also increasingly seen as key agents in addressing 'grand societal challenges' (De Silva et al., 2021; Fini et al., 2018; George et al., 2016). At the same time, their businesses tend to be more complex, subject to stronger technological and market uncertainties than other high-growth startups, and slower to mature (Fini et al., 2023; Pahnke et al., 2015). As such, they are perceived by investors as more risky than non-academic startups (Mathisen and Rasmussen, 2019; Roche et al., 2020).

Acknowledging these aspects, entrepreneurship programs and initiatives by universities have grown substantially, and policymakers target support measures directly at academic startups (Audretsch and Link, 2012; Ayoub et al., 2017; Lehmann et al., 2024; Rasmussen and Sørheim, 2012; Sandström et al., 2018; Toole and Czarnitzki, 2007).

In this study, we contribute to understanding the direct and indirect benefits of public support for academic startups. For the latter, we consider its signaling value towards Venture Capital (VC) providers. Understanding such indirect effects is of primary importance as VC is a key financial source for the growth of high-tech new ventures (e.g., Bertoni et al., 2011; Grilli and Murtinu, 2014). Rooting in signaling theory (Spence, 1973), it is argued that being granted public support can act as an informative signal towards investors, which can serve to mitigate information asymmetries between startups and potential founders, and allow investors to invest where they would otherwise not (Lerner, 1999, 2002).

While the signaling effect of public support on follow-on investment finds empirical support for startups in general (Berger and Hottenrott, 2021; Hottenrott and Richstein, 2020; Howell, 2017; Lerner, 1999; Söderblom et al., 2015; Zhao and Ziedonis, 2020), it is not *ex-ante* clear whether this would be equally the case for academic startups. On the one hand, public support should provide a clearer signal for academic startups because they have high technological uncertainty and more complex business models. Since public support decisions are typically informed by experts that focus more on technological potential, an award can help reduce uncertainties in this dimension (Lerner, 1999, 2002; Pahnke et al., 2015; Toole and Czarnitzki, 2007). On the other hand, it is somewhat controversial whether such evaluations

are effective signals of economic potential, considering the limitations of public institutions in assessing quality, or their focus on non-economic goals (Colombo et al., 2016). Moreover, academic startups are subject to other kinds of uncertainties that might not be informed by signals generated by public support. These uncertainties include questions on the commitment of academics towards their ventures (Balven et al., 2018; Fini et al., 2022; Rasmussen and Sørheim, 2012), their goals in academic entrepreneurship (Hahn et al., 2025; Meyer, 2003), and their business acumen (Gubitta et al., 2016; Mathisen and Rasmussen, 2019; Rasmussen et al., 2011; Wright et al., 2006). Finally, it is an open question whether the signaling value of attracting public support might be different in the context of academic entrepreneurship, as academic researchers are expected to be able to attract public support in the context of funding their research activities (Toole and Czarnitzki, 2007).

Despite these potential tensions, and despite the importance of effective policy towards academic startups for bringing scientific advances into commercial use (Sandström et al., 2018), existing literature has not addressed whether the signal of public support on investment would be different in the context of academic startups. Existing studies drawing on signaling theory focus on IPO valuation of academic startups (Bonardo et al., 2011; Colombo et al., 2019), or look at funding dynamics within cohorts of academic startups (Fini et al., 2023; Gubitta et al., 2016) or within publicly supported firms (Toole and Czarnitzki, 2007). While these studies hint at the existence of a signal, we explicitly compare signaling for academic startups to non-academic startups, allowing us to draw conclusions on the relative strength of these signals.

We base our analysis on the IAB/ZEW Startup Panel, a longitudinal annual survey of startups in Germany enriched with data on equity investments. The Panel presents a unique source of information allowing us to study a large sample of new companies over time, as it is one of the few data sources in the world that collects longitudinal data on startups on variables useful in entrepreneurship research (Gottschalk et al., 2025). The German context is, moreover, an interesting one for studying issues of academic entrepreneurship, as it is a country with strongly developed academic science and where academic entrepreneurship features prominently in science policy (Lehmann et al., 2024). The results confirm the existence of a signaling effect in general. However, this signal is much stronger for academic startups, confirming that public support provides a useful signal for investors and improves access to financing for science-based startups.

In addition, we show that, among academic startups, signals are strongest among

high-tech manufacturing startups. This is in line with the idea that public support delivers the most valuable signal in highly complex and uncertain industries (Kask and Linton, 2023; Nedayvoda et al., 2021; Tech, 2018). At the same time, we find that, for non-academic startups, public support signals matter less in high-tech manufacturing, but are strong for software firms and knowledge-intensive services. This result thus – indirectly – supports the notion that public support signals are interpreted differently for academic startups and other startups. We also show that the signal value of public support is stronger for business angel (BA) investors than for corporate VCs or independent VC funds, in line with the idea that BAs are more receptive to heuristic quality signals in their funding decisions (Berger and Hottenrott, 2021; Maxwell et al., 2011). Finally, we show that the signal is immediate in the sense that it lasts up to one year after receiving the public support, which is in line with a time-restrictive certification mechanism (Islam et al., 2018).

Our study contributes to a better understanding of the opportunities and challenges faced by academic entrepreneurs and the role public startup support policies play in fostering academic startups. Our findings have implications for academic researchers, policymakers, and managers. First, it contributes to the literature on the value of public support for initiating follow-on investments. Second, it allows policymakers to have a better understanding of the impact of their public support programs and shows them opportunities to stimulate academic entrepreneurship, which is often argued to be crucial for diffusing scientific breakthroughs. Third, it helps universities with their support programs and university-linked accelerators in offering the best guidance for academic startups. Lastly, it provides entrepreneurs with a viable option to increase their chances in the search of securing equity investments.

2.2 THEORY DEVELOPMENT

2.2.1 Public support as a signal towards investors

Startups –especially in continental Europe– often experience difficulties obtaining external financing (Audretsch and Lehmann, 2004; Freel, 2007; Grilli and Murtinu, 2014; Himmelberg and Petersen, 1994). This has, in large parts, been attributed to information asymmetries between entrepreneurs and potential investors and the liability of newness (Stinchcombe, 1965). To address the under-provision of early-stage financing, policy programs that target startups are intended to step in, often in

the form of direct financial support such as grants, with a large literature assessing its effectiveness for innovation and economic performance (e.g., Ayoub et al., 2017; Biancalani et al., 2022; Colombo et al., 2013, 2011; Conti, 2018; Hottenrott and Richstein, 2020; Howell, 2017; Söderblom et al., 2015).

Beyond these first-order impacts, researchers have pointed out that public support also leads to follow-on investments (Berger and Hottenrott, 2021; Hottenrott and Richstein, 2020; Howell, 2017; Islam et al., 2018; Lerner, 1999, 2002; Söderblom et al., 2015; Toole and Turvey, 2009; Zhao and Ziedonis, 2020). Arguments for such second-order effects are usually drawn from signaling theory (Spence, 1973). From this perspective, a signal can help reduce uncertainty when it is transparent and costly for the sender to obtain an indication of the underlying quality. In this situation, a signal can substitute for observed quality, allowing a third party to make an informed decision. Applied to the setting of startups and VC investment, it is argued that, in order to make informed decisions, VCs partially rely on indirect information when they cannot directly observe or it is hard to assess the quality of a startup (Stuart et al., 1999). In this regard, public support certifies the quality of granted firms, thereby mitigating information asymmetries through informative signals, leading investors to invest when they otherwise would not (Lerner, 1999, 2002).[2]

Whereas the signaling of public support to investors finds empirical support (Berger and Hottenrott, 2021; Hottenrott and Richstein, 2020; Howell, 2017; Lerner, 1999; Söderblom et al., 2015; Zhao and Ziedonis, 2020), the underlying mechanism has been subject to further discussion. A first criticism of certification theory is that its efficacy critically depends on the quality of the underlying signal, which in turn depends on the ability of the granting organization to screen out high-quality applicants. This is especially salient as VCs are able to carry out high-quality evaluations of potential investment targets (Shepherd, 1999). In this sense, it is a key question whether governmental actors are better able to screen out high-quality firms than VCs, especially because the dimensions on which government funding agencies value firms might be broader than those of private investors, for instance, also including non-financial factors such as societal impact (Colombo et al., 2016). Furthermore, Colombo et al. (2016) raise the point that public support might fail in leading to more investment when the public support crowds out investment, i.e.,

[2]This effect has also been described as the 'halo effect', which indicates that investors might conclude that businesses are generally attractive based on a single positive characteristic (in this case, public early-stage investment) (e.g., Feldman and Kelley, 2003).

when supported firms do not seek investors because they have no further need for financing.

Bianchi et al. (2019) develop a framework to better understand the signal value of subsidies. Based on the classification developed by Connelly et al. (2011), they distinguish *pointing* signals and *activating* signals. Pointing signals are generated by granting support, independent of the value of the support, and serve to distinguish recipients from others. Activating signals are generated by the value of the support, which allows the firm to further activate their quality signal, for instance, by further developing their venture, thereby reducing uncertainties. It might also be the case that the venture becomes more attractive for investors because the public support allows for some measure of financing risk-sharing. Finally, achieving public support might signal the founder's commitment towards the venture, reassuring investors about future efforts (Busenitz et al., 2005; Prasad et al., 2001).

In the context of the U.S. Small Business Innovation Research (SBIR) program, Howell (2017) concludes that pure certification is unlikely to explain the effect an SBIR grant has on follow-on financing. Rather, she finds that the grant allows firms to develop their projects and to reach a proof-of-concept stage, in line with an activating signal. This finding is in line with earlier insights by Toole and Turvey (2009), who show that public support increases the initial endowment of the startup and, therefore, increases the likelihood of follow-on VC investments.

2.2.2 Academic entrepreneurship, public support, and VC

The typical characteristics of academic startups carry some peculiarities that set them apart – positively and negatively – in their relation to venture capital, and how the chances of attracting venture capital are affected by public support.[3] A first dimension in which academic startups differ from others is that academic startups are often highly innovative startups (Bonardo et al., 2011; Tartari and Stern, 2021), with a higher relative importance of intangible assets because of high founder human capital (Gubitta et al., 2016). Compared to other high-growth startups, however, the more complex science base of academic startups creates greater technological and market uncertainties (Pahnke et al., 2015). Academic startups are also often more immature at founding, and hence subject to a longer and less predictable investment horizon (Camuffo et al., 2020; Fini et al., 2023; Mathisen and Rasmussen,

[3]It is relevant that there is no evidence for a general bias from VCs against academic startups. Rather, lower funding rates are likely due to the different characteristics of academic startups (Munari and Toschi, 2011).

2019; Nedayvoda et al., 2021; Toole and Czarnitzki, 2007; Wright et al., 2006). As VCs tend to prefer funding opportunities that are near-to-market (Shane, 2004), this means that, other factors being equal, academic startups can be perceived as more risky by VCs than comparable non-academic firms (Mathisen and Rasmussen, 2019; Roche et al., 2020).[4] At the same time, recent research points out that VCs are more focused on the upside potential than on the downside risk in initial financing rounds, potentially attenuating the effect of such risk (perceptions) (Hao et al., 2025).

From the perspective that the higher riskiness of academic startups might deter VCs, public support can be more beneficial for academic startups as a bridge to future funding opportunities, as such programs have the freedom to underweigh uncertainty in their funding decisions (Toole and Czarnitzki, 2007).[5] Moreover, it has been argued that public funding bodies are the best suited to evaluate such technologies since they provide evaluations by knowledgeable experts and can hence reduce technological uncertainty through funding decisions (Lerner, 1999, 2002; Pahnke et al., 2015). To the extent that academic startups suffer from higher technological uncertainty, they will benefit more from reducing said uncertainty. This effect is possibly further amplified if the startup carries a high potential market impact that is overshadowed by high technological uncertainty before funding. Thus, specifically for academic entrepreneurs subject to high technological uncertainty and long maturation times, differences between evaluation criteria of grant panels and VCs (Colombo et al., 2016) might be a useful boon, not a cost.

At the same time, it is also argued that academic startups are more likely to attract investment because they are more likely to be based on cutting-edge research. Hsu (2007) finds, in the internet industry, that founders with doctoral degrees are more likely to attract VC funding. In the context of IPOs, university-based firms (Bonardo et al., 2011) and biotech firms based on research developed at prestigious universities (Colombo et al., 2019) achieve higher valuations. Compared to our setting of VC, it is relevant to note that the focus on IPOs might lead to findings that are more positive, as public offerings tend to happen when the firm is more mature (Ewens and Farre-Mensa, 2020), when most of the potential uncertainty associated with science-based ventures is already resolved.

[4] Acknowledging these issues, some support programs are aimed specifically at academic startups (Ayoub et al., 2017; Rasmussen and Sørheim, 2012; Sandström et al., 2018).

[5] Toole and Czarnitzki (2007) explore this, taking a real options theory perspective, in the context of the U.S. SBIR program. From this perspective, higher uncertainty pushes back funding from private funders.

Second, academic startups are subject to more uncertainties in the management team. By their nature, academic entrepreneurs are (or were) often in the first place academic scholars and only in the second place entrepreneurs. This leaves further uncertainty for potential investors regarding whether academic founders intend to remain academic scientists or would sufficiently commit to their ventures (Balven et al., 2018; Fini et al., 2022; Rasmussen and Sørheim, 2012). In this aspect, attracting public support might act as a commitment signal (Busenitz et al., 2005; Prasad et al., 2001) for focusing on entrepreneurial activity. In that respect, recent literature points out that academic entrepreneurs can be thought of as a form of hybrid venture, balancing business and academic goals that can hinder each other when not properly managed (e.g., Hahn et al., 2025). Meyer (2003) highlights the notion of the *"entrepreneurial academic"* (as opposed to the academic entrepreneur) who pursues academic entrepreneurship as an alternative avenue for achieving research goals. Closely related, academic entrepreneurs tend to lack business experience, requiring greater monitoring and guidance efforts from VC investors (Gubitta et al., 2016; Mathisen and Rasmussen, 2019; Wright et al., 2006). They also tend to lack critical competencies for credibility as entrepreneurs and need to either develop them through experience or attract them through partnerships in order to convince investors or other stakeholders (Rasmussen et al., 2011).

Third, academic entrepreneurs might have an advantage in attracting public funding from their experience in that domain (Toole and Czarnitzki, 2007). Therefore, when confronted with barriers to equity funding, academic entrepreneurs might be able to use public support mechanisms as a (temporary) substitute. However, it might then be the case that higher skill in grantsmanship acts as a disincentive for developing the skills needed to attract equity funding, damaging growth in the long run.

The few existing studies that are attempting to uncover a signaling effect of public support on VC among academic startups shed partial light on the dynamics between academic entrepreneurship, public funding, and VC, but not fully. Toole and Czarnitzki (2007) study biomedical scientists, and show that, among firms supported by the SBIR program, academic entrepreneurs are more likely to receive VC funding. However, they do not trace whether the incidence of VC changes after SBIR funding, and as such, cannot study the signaling effect of the program, and do not compare the effect of SBIR support for academic entrepreneurs with that for others. Fini et al. (2023) and Gubitta et al. (2016) both study a cohort of academic startups, and compare the effect of a specific public funding program (respectively,

SBIR and TTO funding) on follow-on VC funding within a cohort of academic startups. While both studies document some positive effects, they cannot study whether signaling effects are different for academic startups, as they make no comparison to non-academic startups. In this study, we aim to advance this literature in several ways. First, by making a direct comparison between academic startups and non-academic startups and by testing whether academic startups benefit more or less from signaling effects from public support than other startups, we highlight a nuance overlooked in previous analyses. Second, we uncover heterogeneity in the link between public support and VC depending on the start-ups' type of activity. Third, we explore the time persistence of the effect and how it is linked to the type of VC provider.

2.2.3 Main hypothesis

Summarizing the existing literature, it is fairly well established that public support for startups can lead to follow-up investments (Berger and Hottenrott, 2021; Hottenrott and Richstein, 2020; Howell, 2017; Lerner, 1999; Söderblom et al., 2015; Zhao and Ziedonis, 2020). At the same time, there is discussion on the exact nature of the signal, with argumentation on the efficacy of government agencies as credible certifier (Colombo et al., 2016), and on whether public support mainly achieves this through pointing signals or activating signals (Bianchi et al., 2019; Howell, 2017). We start from the existing literature, and hypothesize that public support leads to follow-on financing as a baseline hypothesis:

Hypothesis H1a *Public support has a positive effect on private venture capital investments.*

Zooming in on the difference between academic and non-academic startups as the main contribution of this study, we build on the literature that identified important differences between them. First, academic startups tend to be riskier, because of more uncertainties in terms of technology development and market success (Pahnke et al., 2015) and founding team dynamics and capabilities (e.g., Fini et al., 2022; Gubitta et al., 2016; Rasmussen et al., 2011). They are also subject to longer development horizons (among others, Fini et al., 2023). At the same time, VCs might be attracted to investment opportunities with high upside potential (Hao et al., 2025). In terms of the value of public support as a signal, academic entrepreneurs might be more able to attract support because of their academic capacities, which

might devalue the distinguishing value of the support as a signal, and lower the need to seek out investors (Toole and Czarnitzki, 2007). At the same time, the types of public support that academic entrepreneurs might be skilled at attracting are also those that are more tuned to resolving technological uncertainty (Pahnke et al., 2015), and the public support might also act as a signal of commitment by the founders, reducing uncertainties in this dimension (Busenitz et al., 2005; Fini et al., 2022; Prasad et al., 2001; Rasmussen and Sørheim, 2012).

As such, the signaling effect of public support on follow-on financing might be higher for academic entrepreneurs than for others if certain conditions apply. That is, if technological uncertainty is high and the support provides a signal that resolves this, if the support allows the entrepreneur to develop their venture to a more mature state, thereby also reducing uncertainty, or if there is much uncertainty concerning the commitment by the entrepreneur that is resolved by the support. On the other hand, the signaling effect might also be similar to that of other startups. If this were the case, the effect would still be stronger if the activating signal of public support is sufficiently strong. Although we cannot distinguish these mechanisms formally and considering that the little existing literature leans to positive effects (Fini et al., 2023; Gubitta et al., 2016; Toole and Czarnitzki, 2007), we follow the hints of the early literature and hypothesize that the effect will be stronger:

Hypothesis H1b *The positive effect of public support on private VC investments is stronger for academic startups compared to non-academic startups.*

2.2.4 Moderators: industry and investor type

In what follows, we explore two potential moderators of our main effect. First, we consider how the signal varies by type of business activity, i.e., by industry. Second, on the side of the investor, we study whether there are differences in how the signal affects investment by looking at alternative types of investors.

2.2.4.1 Industry

Complexity, technological uncertainty, and typical financing needs (e.g., Fini et al., 2023; Hottenrott et al., 2018; Nedayvoda et al., 2021; Söderblom et al., 2015), as well as market uncertainty (Islam et al., 2018), vary considerably by industry. In particular, startups in high-tech manufacturing (sometimes referred to as Deep Tech or 'Tough Tech') or knowledge intense-services are characterized by high complexi-

ties, long unpredictable timelines, and significant risk of failure (Kask and Linton, 2023; Nedayvoda et al., 2021; Tech, 2018).[6] At the same time, these industries are among the most reliant on government support and equity finance (e.g., Colombo et al., 2014, 2010). Moreover, startups in emerging industries face higher information asymmetries, as these industries have not yet established norms, values, and practices (Islam et al., 2018). In addition, operational risks can be higher in emerging industries due to the underdeveloped environment of suppliers, manufacturers, and distributors (Murtha et al., 2002).

Hypothesis H2a *Public support has a stronger positive effect on private VC investments for startups in high-tech manufacturing.*

As a result, signals for public support could be more important among high-tech manufacturing startups (Lerner, 2002). Consistent with this literature, Hottenrott et al. (2018) find a higher positive signaling effect of subsidies on bank loans for the high-tech manufacturing industry as a result of higher uncertainty in this sector. In addition, Fini et al. (2023) finds that, among digital university spin-offs (i.e., software), an SBIR award does not attract more VC, while it does for other spin-offs (Fini et al., 2023). Concerning specifically academic startups, the complexities and uncertainties often present in academic startups are likely more pronounced in high-tech manufacturing. Hence, the signaling effects of public support on academic startups in high-tech manufacturing should be even stronger than those for non-academic startups in the same industry. Therefore, we hypothesize:

Hypothesis H2b *Public support has a stronger positive effect on private VC investments for academic startups in the high-tech manufacturing industry compared to academic startups in other industries.*

2.2.4.2 VC investor type

Second, we argue that the effects of public support signals differ depending on the type of investor receiving the signal. In particular, we distinguish business angels (BAs), corporate VCs (CVCs), and independent VCs (IVCs). These investors have different perspectives, goals, investment criteria, levels of involvement, and

[6] In the empirical analysis, we apply the sector classification by Galindo-Rueda and Verger (2016) and divide the 11 initial industries into aggregated categories. Since Galindo-Rueda and Verger (2016) distinguish the software industry from other services, we also create a separate group for software companies. For the purpose of our study, we still consider the software industry as a knowledge-intensive services industry.

capabilities (Bertoni et al., 2011; Ehrlich et al., 1994; Mason and Stark, 2004). Independent VCs typically try to maximize the return on investment (Hsu et al., 2014). Although business angels and corporate VCs can have the same goal, BAs can also invest out of personal interests, and CVCs can also serve to fulfill strategic goals for the managing corporation (Berger and Hottenrott, 2021; Hsu et al., 2014; Riyanto and Schwienbacher, 2006). From this perspective, we argue that IVCs are more likely to be sensitive to uncertain funding timelines and to benefit more from a signal than BAs or CVCs.

However, another – perhaps stronger – difference between these investors is their capability for screening and due diligence. Traditional VC is known for its rigorous due diligence processes in which possible investment projects are carefully screened (Gompers et al., 2020; Kaplan and Strömberg, 2001, 2004). In contrast, business angels tend to have fewer capacities in this dimension and tend to be more guided by heuristics in their assessment of potential investment options (Berger and Hottenrott, 2021; Fiet, 1995; Maxwell et al., 2011; Van Osnabrugge, 2000). Thus, compared to BAs, VCs should require fewer quality signals because of their stronger formalized screening and due diligence processes. At the same time, BAs tend to require less due diligence before making a funding decision, and prior research has found a stronger signal effect for BAs than VCs (Berger and Hottenrott, 2021). These differences imply that – again assuming higher uncertainties for academic startups than non-academic startups – BAs would benefit more from a signal than IVCs or CVCs, as they are more reliant on heuristics in investment decisions.

Therefore, we hypothesize:

Hypothesis H3a *Public support has a larger positive effect on investment by BA compared to investment by IVC or CVC.*

Hypothesis H3b *Public support for academic startups has a larger positive effect on investment by BA compared to investment by IVC or CVC.*

2.2.5 Analysis of time persistency

Lastly, we explore whether the signal endures after receiving governmental support. Theory suggests that, given the quickly changing nature of early new ventures, signals surrounding their quality will quickly lose relevance. Islam et al. (2018) find that the signal of a grant dissipates six months after the receipt of the government grant. This is in line with the attention-based view, where the value of a signal

diminishes when information updates and the context changes (Berger and Hottenrott, 2021; Feldman and Kelley, 2003). Similarly, Pollock et al. (2010) highlight the importance of new information provided by prestigious affiliates, such as executives, directors, underwriters, and VCs, in an information-asymmetric environment. However, the signal value of adding additional prestigious VCs and underwriters is subject to diminishing effects.

Hypothesis H4a *Public support has a time-limited positive influence on private VC investments.*

Specifically for academic start-ups, public support signals might also reduce uncertainty about the commitment of academic entrepreneurs (Busenitz et al., 2005; Prasad et al., 2001), which can be a more pressing concern than for other startups (Fini et al., 2022; Rasmussen and Sørheim, 2012). When such uncertainty is resolved by the signal, it might have a more persistent effect on funding chances. As a result, we propose the following hypotheses:

Hypothesis H4b *Public support has a more persistent positive influence on private VC investments for academic startups than for other startups.*

2.3 DATA AND METHOD

2.3.1 Data

The analysis draws on data from the IAB/ZEW Startup Panel in Germany. This panel is based on a computer-assisted telephone survey conducted annually with 5,000 to 6,000 start-ups and is coordinated by the Centre for European Economic Research (ZEW). The survey sample is selected through stratified random sampling from the full population of newly registered firms in Germany, and includes all economic sectors except agriculture, mining, and the public sector. Participating firms can be surveyed for up to seven consecutive years. The initial wave gathers comprehensive information about the founding process and the founders (including demographics, prior experience, team background, and entrepreneurial orientation), while the subsequent panel waves track innovation activities and a range of firm-level outcomes over time. The data is available through the research data center of ZEW (Gottschalk et al., 2025). We enrich the Startup panel with data on VC investment. We obtain the VC investment through transaction data from two primary data

sources, Bureau van Dijk's Zephyr database and Majunke Consulting (Berger and Hottenrott, 2021).

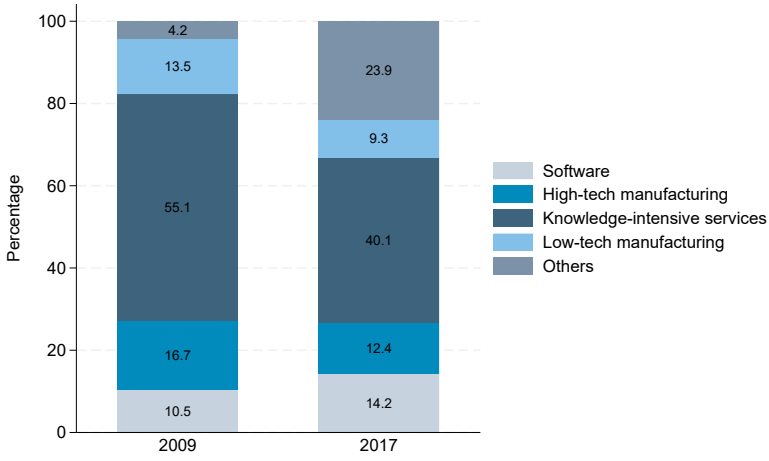
We use the survey waves from 2009 until 2017 from the IAB/ZEW Startup Panel and have additional VC transactional data until 2019. We exclude firms that are corporate spinoffs, franchises, or joint ventures. The final sample consists of 6,670 startups founded between 2007 and 2017, including 1,557 academic startups and 5,113 non-academic startups.

2.3.2 Variables

2.3.2.1 Dependent variables

The main dependent variable is *private VC*, which indicates whether and when the firm received any type of private venture capital funding: business angels, independent VC, or corporate VC. The variables are coded as a binary variables that switch from 0 to 1 in the year when the firm receives private VC for the first time, and keeps the value one afterwards.[7] 10.28% of the total number of firms in our sample receive private VC investments at some point in time, with 8.66% of the non-academic startups and 15.61% of the academic startups. Figure 2.1 shows the distribution of VC across sectors.

Figure 2.1: Distribution of VC by sector



[7]For the timing analysis, Private VC is recoded to 0 in the years they did not receive the private VC investment and 1 in the year they received the private VC investment.

The sources of private VC are also used as individual dependent variables, with 8.48% of the startups having received investments from business angels, 3.22% from independent VC, and 1.95% from corporate VC.

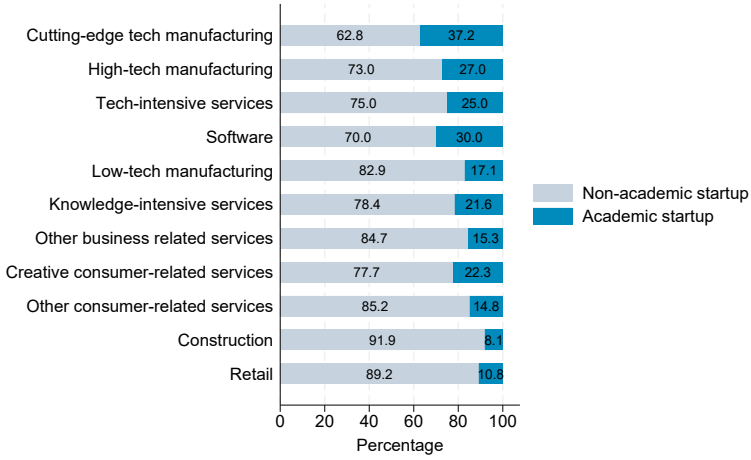
2.3.2.2 Independent variables

The first independent variable is the time-invariant dummy variable, *Academic*. To delineate which start-ups can be considered academic, we rely on a survey question that asks whether at least one founder has worked at a university or research institution, excluding roles like teaching assistants and interns. The definition of academic startups has been ambiguous in the literature, with terms like university spin-offs, academic spin-offs, university spin-outs, academic startups, and university startups used interchangeably. Some have attempted to clarify these definitions by identifying key dimensions such as the status of the founders, the nature of the knowledge transferred, institutional origin, and sponsorship (e.g., Mathisen and Rasmussen, 2019; Pirnay et al., 2003). Academic entrepreneurs are often defined by the presence of university-industry knowledge transfer (e.g., Agarwal and Shah, 2014; Shane, 2004), but some definitions emphasize the academic background of the founders rather than specific knowledge transfer (Coad et al., 2021; Fini et al., 2023). Consequently, two main strands exist in the literature: a broader category including any startup with academic founders, termed "academic startups" or "university startup entrepreneurs" (Coad et al., 2021; Colombo and Piva, 2008), and a more specific subset requiring direct knowledge transfer, termed "academic spin-offs" or "university spin-offs" (Mathisen and Rasmussen, 2019; Pirnay et al., 2003). Our study adheres to the broader stream. According to this definition of academic entrepreneurship, 23.34% of the total sample are academic startups. Figure 2.2 shows the shares of academic start-ups by industry.

The second independent variable is *Public Support*, a dummy variable that switches from 0 to 1 in the year when the startup, for the first time, reported receiving public support from the government. Public support is an overarching term that allows the government to financially contribute to startups either through governmental subsidies (grants) or public venture capital.[8] 25.81% of the startups have received governmental support, of which 22.84% are non-academic startups

[8]Public VC and subsidies are often used interchangeably in the literature and have diverse contexts concerning their application in the US or EU. Additionally, government VC and subsidies come from the same funding source, the government. Our data allows us to separate support through public subsidies and public VC. The vast majority (96.23%) stems from public subsidies. The results are robust to dropping public VC from the sample, see Tables 2.4, A2, A3, A4.

Figure 2.2: Shares of academic start-ups by industry



and 35.58% are academic startups.

2.3.2.3 Control variables

We control for a number of factors that can affect the probability of obtaining public support as well as the probability of obtaining private VC. As we mainly rely on fixed-effects regression models, sources of time-invariant heterogeneity are controlled for. Nevertheless, we still control for some sources of time-variant heterogeneity, and also present pooled OLS models with extensive time-invariant control variables. Note that most founders and firm characteristics are categorical indicators. This follows from the survey design as a telephone survey, where it is often impractical to ask for detailed numerical values (see Gottschalk et al., 2025).

2.3.2.3.1 Time-variant control variables We include three time-variant control variables, *Export*, *Market Novelty*, and *Firm size* from the Startup Panel. They, respectively, reflect the competitiveness, innovativeness, and size of the firm. *Export* is a dummy variable that takes the value one when the startup generates profits due to export in the relevant year. *Market Novelty* is a dummy variable that takes the value one when the startup introduces a market novelty at a regional, national, or global level in the relevant year. The question is asked as part of the survey in a wording similar to that used in the Community Innovation Surveys (CIS). Lastly,

Firm size is taken into account as a categorical variable: no full-time employees (0), 1-10 full-time employees (1), and $>$ 10 full-time employees (2).

2.3.2.3.2 Time-invariant control variables In specifications with firm fixed effects, time-invariant sources of heterogeneity are absorbed. In specifications without fixed effects, we include the following control variables from the Startup Panel to account for observable sources of time-invariant heterogeneity. First, *Industry* is a categorical variable including 11 German industry classifications according to the classification of economic sectors by the federal statistical office (Gottschalk et al., 2025). Second, we also control for founder education through a set of dummies that take the value one when at least one of the founders has obtained a higher education degree in, respectively, Science, Engineering, Social Sciences, Humanities and Arts, and Other fields. Third, we control for regional differences in funding patterns by including dummies for start-ups located in the former East Germany and Berlin. Fourth, we control for founder team characteristics through several variables. *Team* is a dummy variable that takes the value of one for startups that have more than one founder in the founding team. Fifth, *Female* is a dummy variable that takes the value of one for founding teams with at least one female founder. *Founder(s) age* is constructed as the average of the ages of the youngest and oldest members of the founding team. *Number of patents* before founding indicates how many patents the founders started their company with. We only consider patents before founding because start-up patenting has been shown to be driven by VC investment (Heller, 2024). Using the initial number of patents avoids that our specifications are affected by reverse causality. *Startup Experience* is a dummy representing whether one of the founders has previously ever founded one or several firms before the start-up of this firm. The years of industry experience for the founder with the longest experience are taken into account in *Industry Experience*. *R&D activity* refers to whether startups had research and development (R&D) activities or not. *Opportunity entrepreneurship* captures whether the startup was founded to exploit an opportunity or out of necessity, controlling for possible differences in founding motive between academic and non-academic startups. In addition, *Unemployment before startup* indicates if one of the founders was unemployed right before the founding of the firm. Lastly, the *Founding years* of the startups are incorporated and range from 2007 to 2017. Table 3.1 provides an overview of the main variables.

Table 2.1: Summary statistics

	count	mean	sd	min	max
Private VC	17739	0.082	0.275	0	1
Business Angel	17739	0.067	0.250	0	1
Corporate VC	17739	0.013	0.113	0	1
Independent VC	17739	0.025	0.157	0	1
Public support	17739	0.302	0.459	0	1
Public support x Academic	17739	0.092	0.289	0	1
Subsidies	17739	0.291	0.454	0	1
Government VC	17739	0.034	0.180	0	1
Academic	17739	0.244	0.429	0	1
Industry = cutting-edge tech manufacturing	17739	0.080	0.272	0	1
Industry = high-tech manufacturing	17739	0.080	0.271	0	1
Industry = tech-intensive services	17739	0.306	0.461	0	1
Industry = software	17739	0.129	0.336	0	1
Industry = low-tech manufacturing	17739	0.073	0.261	0	1
Industry = knowledge-intensive services	17739	0.140	0.347	0	1
Industry = other business related services	17739	0.057	0.232	0	1
Industry = creative consumer-related services	17739	0.054	0.226	0	1
Industry = other consumer-related services	17739	0.021	0.143	0	1
Industry = construction	17739	0.032	0.176	0	1
Industry = retail	17739	0.027	0.162	0	1
Average founding year	17739	2012.326	2.661	2007	2017
Education Science	17656	0.251	0.434	0	1
Education Engineering	17656	0.439	0.496	0	1
Education Social Sciences	17656	0.411	0.492	0	1
Education Humanities and Arts	17656	0.085	0.279	0	1
Education Other fields	17656	0.012	0.109	0	1
Region = West	17731	0.803	0.398	0	1
Region = Berlin	17731	0.064	0.245	0	1
Region = East	17731	0.133	0.339	0	1
Team	17730	0.484	0.500	0	1
Female	17739	0.199	0.400	0	1
Founder(s) age	17618	42.851	9.413	19	95
Number of patents before founding	17688	0.337	3.989	0	180
Startup Experience	17725	0.517	0.500	0	1
Industry Experience	17637	14.518	9.964	1	60
R&D activity	17738	0.266	0.442	0	1
Opportunity Entrepreneurship	17739	0.869	0.337	0	1
Unemployment before startup	17708	0.085	0.279	0	1
Market Novelty	17739	0.205	0.404	0	1
Export	17739	0.262	0.440	0	1
No full-time employees	17739	0.521	0.500	0	1
1-10 full-time employees	17739	0.393	0.488	0	1
>10 full-time employees	17739	0.086	0.280	0	1
Year	17739	2014.237	2.170	2009	2017

2.3.3 Empirical strategy

We estimate the following benchmark model:

$$\begin{aligned} Private\ VC_{it} = \beta_1 * Public\ Support_{it} + \beta_2 * Public\ Support\ x\ Academic_{it} \\ +\delta * X_{it} + c_i + \varepsilon_{it} \end{aligned} \tag{2.1}$$

In the benchmark model, *Private VC* denotes the outcome variable, whether or not the firm has (or had) attracted VC in year t. c_i represent firm fixed effects, and ε_{it} represents the error term. *Public Support* indicates whether a startup received public support by a given year. Note that this information is based on yearly reporting by the startups. In the main models, we specify both *Private VC* and *Public Support* to occur in the same year, but we also estimate a model in the robustness checks where we lag *Public Support* by one full year to account for the possibility that the VC funding occurred earlier in the year than the subsidy receipt. β_1 represents the increase in the probability of obtaining VC investments due to public support for a startup. The key variable of interest is *Public Support x Academic*, which indicates academic startups that have received public support. Given the interaction effect, *Public Support x Academic*, the coefficient β_1 represents the effect of public support for non-academic startups. β_2 shows the additional effect public support has on academic startups. X_{it} represents time-variant control variables.

We estimate the model as described above, including startup fixed effects, and additionally present pooled ordinary least squares (POLS) specifications where X_{it} also includes the time-invariant control variables described above. The fixed effects model has the advantage that it accounts for unobserved time-invariant heterogeneity. To the extent that endogeneity issues are driven by, e.g., unobserved differences in venture quality, for instance, because of high-potential ideas, these should thus be resolved by the FE model. We cluster standard errors by startup. At the same time, the POLS is still informative as it also captures between-firm variation.

In the empirical analyses, the benchmark model is extended in three ways to answer the additional research questions. First, the model is estimated for different subsamples according to five industry classes, in line with the classification by Galindo-Rueda and Verger (2016) (i.e., high-tech manufacturing, software, knowledge-intensive services, low-tech manufacturing, and others), and might identify divergent effects of public support regarding the industry. Second, the benchmark model is estimated separately for the different sources of private VC (BA,

CVC, and IVC). This model allows for a more detailed understanding of the effect public support has on each type of private VC investor. Third, the model is extended by including lagged variables and a forward variable for the independent variables, *Public Support* and *Public Support x Academic*. This allows specifying the timing between obtaining public support and private VC, which allows for a specification in which public support influences the probability of receiving private VC in subsequent years.

As a final analysis, the panel dataset is reduced to a cross-sectional format, including the time-invariant control variables. The funding outcomes are recombined into a single categorical variable, *Funding*. *Funding* takes on different values depending on whether the firm receives public support and/or private VC and their relative timing. The first category, "No funding," implies that the startup has not received public support or private VC. The second category, "Only private VC," means that the startups received private VC but no public support. The third category, "Private VC first," implies that the startups first received private VC and that at least one year later, the startup received public support. The fourth category, "Only public support," means that the startups received public support but no private VC financing. The fifth category, "Public support first," implies that the startup received public support at least one year before receiving private VC investments. The last category, "Private and public together," means that the startup received public support and private VC in the same year.

We then use a multinomial logit model to estimate the probability of receiving a certain funding outcome for academic and non-academic startups. First, the two groups, non-academic and academic startups, are balanced by using entropy balancing, which stochastically assigns weights to the observations in the control sample and results in similar moments for the control and treatment group variables, which improves comparability (Hainmueller, 2012). Second, the multinomial logit is conducted for academic startups (*Academic*) and the time-invariant controls on the outcome variable, *Funding*. The approach allows for a deeper understanding of the complex relationship between public and private funding and their relative timing with respect to each other. Furthermore, it permits a simple interpretation regarding the selection effect of academics into public subsidies (possibly due to acquired grant writing skills (Mathisen and Rasmussen, 2019) or exposure to more opportunities). Additionally, the multinomial logit can confirm and add more weight to the initial findings in the FE and POLS specifications concerning the role of public support in the ability to attract follow-on investments.

2.4 RESULTS

2.4.1 Main results

Table 2.2 shows the results of the benchmark model. Models (1) and (2) include firm fixed effects. Model (2) adds time-variant control variables to the specification. Models (3) and (4) instead use a pooled ordinary least squares (POLS) specification, without controls for model (3) and with controls for model (4).[9] Across these models, the coefficients of interest are those of *Public Support* and *Public Support x Academic*. The former captures the difference in the probability of attracting VC investment once the startup has attracted public support (Hypothesis H1a). The latter captures the additional impact of public support on the probability of receiving private VC investment for academic startups (Hypothesis H1b).

In model (1), the coefficient of *Public support* is positive and significant ($p < 0.01$), indicating that receiving public support increases the probability of receiving private VC by approximately 7.4%. The coefficient of *Public Support x Academic* is also positive and significant ($p < 0.01$), indicating that academic startups that receive public support have a 10.5% higher probability of receiving private VC than non-academic startups. These coefficients remain comparable, at respectively 6.7% and 10.0% in model (2). The POLS specifications of models (3) and (4) yield similar conclusions. The results thus show that startups are more likely to attain private VC investment after receiving government support, and that this effect is larger for academic startups than for non-academic startups, confirming hypotheses H1a and H1b.

Concerning the control variables, we observe expected positive relations between VC investment and market novelty and exports in model (2). Note that the negative coefficient of firms with more than 10 full-time employees conditions on the firm fixed effect, and should be interpreted as the probability of VC declines as the firm grows, conditional on (unobserved) firm quality. In the POLS model (model (4)), the coefficients of firm size are positive. Regarding the other controls, we find that higher private VC chances are associated with R&D activities, team-founded startups, being situated in Berlin, and startups in the social sciences. More founder industry experience is associated with a lower probability of receiving private VC.

[9]Note that, due to data constraints, model (4) is based on a slightly lower number of observations than models (1)-(3). This is due to a lower number of observations for some time-invariant control variables (e.g., *Education, Founder(s) age*, and *Industry experience).*

Table 2.2: Main results for public support and private VC for academic startups

	Private VC			
	(1) FE	(2) FE	(3) POLS	(4) POLS
Public Support	0.0744***	0.0669***	0.0282***	0.0439***
	(0.0152)	(0.0149)	(0.0082)	(0.0089)
Public Support x Academic	0.1053***	0.1001***	0.1479***	0.1019***
	(0.0314)	(0.0307)	(0.0213)	(0.0198)
Academic			0.0055	-0.0120
			(0.0082)	(0.0083)
Market Novelty		0.0188***		0.0349***
		(0.0045)		(0.0072)
Export		0.0289***		0.0154**
		(0.0063)		(0.0076)
1-10 full-time employees		0.0027		0.0363***
		(0.0054)		(0.0061)
>10 full-time employees		-0.0234**		0.0342***
		(0.0101)		(0.0117)
Education Science				0.0099
				(0.0118)
Education Engineering				0.0071
				(0.0118)
Education Social Sciences				0.0494***
				(0.0114)
Education Humanities and Arts				-0.0082
				(0.0127)
Education Other fields				0.0042
				(0.0265)
Berlin				0.0486***
				(0.0153)
East				-0.0215**
				(0.0092)
Team				0.0288***
				(0.0073)
Female				-0.0072
				(0.0089)
Founder(s) age				0.0001
				(0.0004)
Number of patents before founding				-0.0004
				(0.0005)
Startup Experience				0.0105
				(0.0067)
Industry Experience				-0.0011***
				(0.0004)
R&D activity				0.0651***
				(0.0096)
Opportunity Entrepreneurship				0.0075
				(0.0090)
Unemployment before startup				-0.0153
				(0.0109)
Firm FE	YES	YES	/	/
Time FE	YES	YES	/	YES
Industry FE	/	/	/	YES
Founding year FE	/	/	/	YES
Observations	17739	17739	17739	16680
Groups (Firms)	6670	6670	6670	6519
R^2	0.0753	0.0828	0.0352	0.1174

Note: Standard errors in parentheses. Standard errors clustered by firm. Stars indicate significance levels: * p<0.1, ** p<0.05, *** p<0.01.

2.4.2 Main model: robustness tests

We present additional tests to assess the robustness of the findings in Table 2.3. First, we account for the possibility that our results are attenuated by survival bias. Therefore, we correct for this by including an inverse Mills ratio, based on the likelihood of insolvency, in the main model. Column (1) presents the first-stage Probit model, which shows that academic startups are not significantly more or less likely to become insolvent. Column (2) then shows that our results are robust to including the inverse Mills ratio.[10]

Second, we address the concern that academic and non-academic startups might not be comparable in terms of important characteristics. To mitigate this concern, we apply entropy balancing. Entropy balancing is a statistical reweighting method used to adjust the distribution of covariates between groups to ensure they are similar (Hainmueller, 2012). In this exercise, we account for founding team characteristics and other firm characteristics at founding.[11] Columns (3) and (4) in Table 2.3 show the results with balanced data. Our conclusions remain robust.

Third, we address the concern that our results might be driven by simultaneity between public support and VC. To mitigate this, we show in columns (5) and (6) of Table 2.3 a specification with lagged independent variables, $Public\ Support_{t-1}$ and $Public\ Support\ x\ Academic_{t-1}$. The results are robust for this specification.

Fourth, we account for potential heterogeneity in public support. In particular, we distinguish public support in the form of subsidies, and public support in the form of Government Venture Capital (GVC) investments. Columns (1), (2), (3), and (4) of Table 2.4 show the results when considering subsidies, while columns (5) and (6) use GVC. The results using subsidies resemble the main results [12]. The results for GVC are more volatile, likely because of their lower prevalence, and yield an insignificant coefficient in the FE specification. The coefficient remains significant in the POLS specification.

Fifth, we conduct robustness checks regarding the definition of academic startups. One alternative definition of academic startups could be to consider a startup as academic when at least one PhD holder is on the founding team. Columns (1) and (2) of Table 2.5 show the original results for comparison purposes. Columns (3) and (4) present the results when academic startups are defined as having at least

[10] As the fixed effects model does not allow us to include time-invariant variables, we only present the POLS model.

[11] The results of this balancing are shown in the appendix in Table A5.

[12] Additionally, we show the moderator analyses concerning the industry and VC type, and the time persistency analysis considering only subsidies and the interaction term in Tables A2, A3, A4

Table 2.3: Alternative specifications

	Insolvency	Private VC				
		Mills ratio	Matching		Lagged	
	(1) Probit	(2) POLS	(3) FE	(4) POLS	(5) FE	(6) POLS
Public Support		0.0439***	0.0801***	0.0704***		
		(0.0089)	(0.0256)	(0.0169)		
Public Support x Academic		0.1016***	0.0802**	0.0776***		
		(0.0198)	(0.0374)	(0.0241)		
Public Support$_{t-1}$					0.0298***	0.0335***
					(0.0108)	(0.0098)
Public Support x Academic$_{t-1}$					0.0640***	0.1140***
					(0.0226)	(0.0232)
Academic	-0.0348	-0.0123		0.0084		-0.0040
	(0.0725)	(0.0083)		(0.0098)		(0.0096)
Export		0.0155**	0.0301***	0.0168	0.0260***	0.0109
		(0.0076)	(0.0098)	(0.0116)	(0.0066)	(0.0084)
Market Novelty		0.0350***	0.0165***	0.0360***	0.0089**	0.0352***
		(0.0072)	(0.0061)	(0.0095)	(0.0044)	(0.0087)
1-10 full-time employees		0.0362***	0.0049	0.0504***	-0.0055	0.0350***
		(0.0061)	(0.0086)	(0.0091)	(0.0054)	(0.0069)
>10 full-time employees		0.0342***	-0.0395***	0.0479***	0.0007	0.0790***
		(0.0117)	(0.0147)	(0.0184)	(0.0171)	(0.0188)
Education Science	-0.0430	0.0095		0.0163		0.0115
	(0.0927)	(0.0118)		(0.0161)		(0.0140)
Education Engineering	-0.0539	0.0066		0.0180		0.0134
	(0.0866)	(0.0119)		(0.0170)		(0.0143)
Education Social Sciences	0.1218	0.0499***		0.0695***		0.0597***
	(0.0827)	(0.0114)		(0.0165)		(0.0139)
Education Humanities and Arts	-0.0856	-0.0084		-0.0219		-0.0024
	(0.1231)	(0.0127)		(0.0172)		(0.0158)
Education Other fields	-0.6189	0.0036		-0.0238		0.0068
	(0.4146)	(0.0265)		(0.0358)		(0.0341)
Berlin	-0.1423	0.0483***		0.0624***		0.0413**
	(0.1250)	(0.0153)		(0.0209)		(0.0179)
East	0.1025	-0.0207**		-0.0235		-0.0154
	(0.0812)	(0.0091)		(0.0162)		(0.0108)
Team	-0.0823	0.0285***		0.0229**		0.0315***
	(0.0661)	(0.0073)		(0.0113)		(0.0087)
Female	-0.1014	-0.0076		-0.0107		-0.0098
	(0.0801)	(0.0089)		(0.0134)		(0.0105)
Founder(s) age	0.0091**	0.0002		0.0005		0.0001
	(0.0036)	(0.0004)		(0.0007)		(0.0005)
Number of patents before founding	-0.0044	-0.0004		-0.0015*		-0.0003
	(0.0117)	(0.0005)		(0.0008)		(0.0006)
Startup Experience	0.1789***	0.0112*		0.0128		0.0109
	(0.0627)	(0.0067)		(0.0105)		(0.0078)
Industry Experience	-0.0038	-0.0012***		-0.0026***		-0.0015***
	(0.0034)	(0.0004)		(0.0008)		(0.0005)
R&D activity	0.2222***	0.0662***		0.0604***		0.0780***
	(0.0669)	(0.0097)		(0.0119)		(0.0117)
Opportunity Entrepreneurship	0.0288	0.0077		0.0070		0.0086
	(0.0934)	(0.0090)		(0.0146)		(0.0098)
Unemployment before startup	0.0831	-0.0148		-0.0295		-0.0065
	(0.1070)	(0.0109)		(0.0194)		(0.0125)
Inverse Mills ratio - Insolvency		-0.1128		-0.3099		-0.0169
		(0.1614)		(0.3556)		(0.2189)
Firm FE	/	/	YES	/	YES	/
Time FE	/	YES	YES	YES	YES	YES
Industry FE	YES	YES	/	YES	/	YES
Founding year FE	/	YES	/	YES	/	YES
Observations	6557	17357	17294	17294	13145	12858
Groups (Firms)	6557	6524	6503	6503	5235	5120
R^2	.0438	0.1167	0.1089	0.1505	0.0569	0.1305

Note: Standard errors in parentheses. Standard errors clustered by firm. Stars indicate significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 2.4: Robustness test with separated subsidies and GVC

	Private VC					
	(1) FE	(2) FE	(3) POLS	(4) POLS	(5) FE	(6) POLS
Subsidies	0.0282***	0.0446***	0.0224***	0.0253***		
	(0.0090)	(0.0136)	(0.0082)	(0.0088)		
Subsidies x Academic	0.1218***	0.1216***	0.1386***	0.0855***		
	(0.0219)	(0.0313)	(0.0209)	(0.0199)		
Government VC					0.3794***	0.3438***
					(0.0566)	(0.0408)
GVC x Academic					-0.0086	0.2140***
					(0.0809)	(0.0572)
Academic			0.0151*	-0.0042		0.0077
			(0.0083)	(0.0088)		(0.0080)
Export		0.0296***		0.0160**	0.0256***	0.0149**
		(0.0063)		(0.0077)	(0.0063)	(0.0073)
Market Novelty		0.0194***		0.0365***	0.0171***	0.0290***
		(0.0045)		(0.0073)	(0.0043)	(0.0068)
1-10 full-time employees		0.0032		0.0387***	0.0017	0.0299***
		(0.0054)		(0.0061)	(0.0053)	(0.0060)
>10 full-time employees		-0.0253**		0.0340***	-0.0266***	0.0163
		(0.0101)		(0.0118)	(0.0101)	(0.0110)
Firm FE	YES	YES	/	/	YES	/
Time FE	YES	YES	/	YES	YES	YES
Industry FE	/	/	/	YES	/	YES
Founding year FE	/	/	/	YES	/	YES
Observations	24237	17739	24237	17357	17747	17361
Groups (Firms)	6709	6670	6709	6524	6678	6528
R^2	0.0677	0.0799	0.0284	0.1088	0.1162	0.1829

Note: The time-invariant variables for the POLS specifications are not shown in this table. Standard errors in parentheses. Standard errors clustered by firm. Stars indicate significance levels: * p<0.1, ** p<0.05, *** p<0.01.

one PhD founder. The results are robust to this re-specification. In columns (5) and (6), we present an additional definition, where we consider a startup as academic when one of the founders (1) has worked at a university or research institution and (2) has obtained a PhD. This is a much stricter definition, as only 36,5% of potential academic startups satisfy both criteria. Here, too, the results are similar, with the less pronounced – and now insignificant – result in the FE specification (column (5)) likely due to the smaller number of academic entrepreneurs using this definition. The coefficient remains positive and significant in the POLS specification.

We present two further robustness tests in the Appendix. First, we account for the possibility that some academic founders gained considerable amounts of industry experience before starting their new ventures. In columns (1) and (2) of Table A1, we only take into account academic startups with an average founding team age under 30. The results remain robust, with larger effect sizes than in the main results. In columns (3) and (4) of Table A1, we only take academic startups into account where the academic founder is still working at the university after the

Table 2.5: Robustness test with alternative definitions of academic startups

	Private VC					
	Researcher definition		PhD definition		Researcher+PhD	
	(1) FE	(2) POLS	(3) FE	(4) POLS	(5) FE	(6) POLS
Public Support	0.0669***	0.0439***	0.0812***	0.0476***	0.0919***	0.0526***
	(0.0149)	(0.0089)	(0.0149)	(0.0085)	(0.0149)	(0.0085)
Public Support x Academic	0.1001***	0.1019***				
	(0.0307)	(0.0198)				
Academic		-0.0120				
		(0.0083)				
Public Support x PhD			0.0857**	0.1387***		
			(0.0342)	(0.0256)		
PhD				-0.0112		
				(0.0112)		
Public Support x Academic & PhD					0.0528	0.1395***
					(0.0358)	(0.0292)
Academic & PhD						-0.0118
						(0.0133)
Export	0.0289***	0.0154**	0.0287***	0.0156**	0.0291***	0.0151**
	(0.0063)	(0.0076)	(0.0063)	(0.0077)	(0.0063)	(0.0077)
Market Novelty	0.0188***	0.0349***	0.0190***	0.0340***	0.0192***	0.0339***
	(0.0045)	(0.0072)	(0.0045)	(0.0072)	(0.0045)	(0.0072)
1-10 full-time employees	0.0027	0.0363***	0.0033	0.0361***	0.0033	0.0358***
	(0.0054)	(0.0061)	(0.0054)	(0.0061)	(0.0054)	(0.0061)
>10 full-time employees	-0.0234**	0.0342***	-0.0235**	0.0334***	-0.0239**	0.0343***
	(0.0101)	(0.0117)	(0.0102)	(0.0116)	(0.0102)	(0.0117)
Firm FE	YES	/	YES	/	YES	/
Time FE	YES	YES	YES	YES	YES	YES
Industry FE	/	YES	/	YES	/	YES
Founding year FE	/	YES	/	YES	/	YES
Observations	17739	17357	17739	17357	17739	17357
Groups (Firms)	6670	6524	6670	6524	6670	6524
R^2	0.0828	0.1166	0.0810	0.1197	0.0792	0.1183

Note: The time-invariant variables for the POLS specifications are not shown in this table. Standard errors in parentheses. Standard errors clustered by firm. Stars indicate significance levels: * p<0.1, ** p<0.05, *** p<0.01.

startup's foundation in comparison to non-academics. The results remain robust, albeit at only 10% significance in the FE specification.

Second, it might be the case that differences in private VC are driven by unaccounted-for differences in financing needs between academic and non-academic startups. To account for this, columns (5) and (6) of Table A1 present specifications controlling for sales as a proxy for available finances. We do not include this variable in the benchmark model as we only observe sales for a subset of the startups. In both the FE and the POLS specification, the results are robust to controlling for sales.

2.4.3 Moderators: industry and investor type

2.4.3.1 Industry

Table 2.6 splits the initial sample in five industries, in line with the classification by Galindo-Rueda and Verger (2016): the software industry (models (1) and (2)), high-tech manufacturing industry ((3) and (4)), knowledge-intensive service industries apart from the software industry (5) and (6)), the low-tech manufacturing industry ((7) and (8)) and other industries ((9) and (10)).

The coefficient for *Public Support* is positive and significant for the software industry and the knowledge-intensive services industry. Public support increases the likelihood of VC in the software industry by 18.4% ($p < 0.01$, model (1)) and in the knowledge-intensive services industry by 3.7% ($p < 0.05$, model (5)). However, we do not find a consistent effect for public support in the high-tech manufacturing industry, with no significant effect in the FE specification but a positive and significant effect, at $p < 0.05$, in the POLS specification. As such, we cannot confirm H2a.

Concerning academic startups, we find that *Public Support x Academic* has a significant positive coefficient of 0.191 ($p < 0.01$, model (3)) in the high-tech industry and in the FE specification. The higher effect of governmental support for academic startups observed in Table 2.2 thus appears mainly driven by academic startups in the high-tech manufacturing industry. We find no robust effects for academic startups in the software industry, knowledge-intensive services, low-tech manufacturing, or other industries. This confirms hypothesis H2b.

Table 2.6: Results by industry

	Private VC									
	Software		High-tech manufacturing		Knowledge-intensive services		Low-tech manufacturing		Others	
	(1) FE	(2) POLS	(3) FE	(4) POLS	(5) FE	(6) POLS	(7) FE	(8) POLS	(9) FE	(10) POLS
Public Support	0.1842***	0.1423***	0.0193	0.0791***	0.0368**	0.0274**	0.0568	0.0060	0.0157	-0.0221
	(0.0532)	(0.0307)	(0.0290)	(0.0270)	(0.0185)	(0.0112)	(0.0380)	(0.0227)	(0.0256)	(0.0192)
Public Support x Academic	-0.0136	0.0401	0.1910***	0.1240**	0.0662	0.0504**	0.0787	0.1461**	0.1022	0.1449**
	(0.0804)	(0.0501)	(0.0594)	(0.0489)	(0.0403)	(0.0248)	(0.0868)	(0.0705)	(0.1300)	(0.0726)
Academic		-0.0328		0.0164		-0.0129		-0.0216		-0.0009
		(0.0200)		(0.0307)		(0.0100)		(0.0303)		(0.0218)
Export	0.0210	0.0101	0.0500***	0.0131	0.0070	-0.0029	0.0700***	0.0644***	-0.0006	0.0473**
	(0.0191)	(0.0203)	(0.0165)	(0.0192)	(0.0056)	(0.0099)	(0.0222)	(0.0235)	(0.0198)	(0.0212)
Market Novelty	0.0264*	0.0629***	0.0214**	-0.0143	0.0132**	0.0400***	0.0328**	0.0486**	-0.0055	0.0337**
	(0.0141)	(0.0180)	(0.0099)	(0.0170)	(0.0056)	(0.0109)	(0.0159)	(0.0193)	(0.0096)	(0.0170)
1-10 full-time employees	0.0059	0.0922***	0.0091	0.0558***	-0.0024	0.0181**	0.0272	0.0302	0.0005	0.0333**
	(0.0177)	(0.0181)	(0.0167)	(0.0196)	(0.0051)	(0.0071)	(0.0218)	(0.0187)	(0.0160)	(0.0158)
>10 full-time employees	-0.0297	0.1329***	-0.0209	0.0642**	-0.0138	0.0168	-0.0161	-0.0128	-0.0043	0.0202
	(0.0304)	(0.0338)	(0.0239)	(0.0320)	(0.0142)	(0.0177)	(0.0300)	(0.0273)	(0.0195)	(0.0212)
Firm FE	YES	/	YES	/	YES	/	YES	/	YES	/
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	/	YES	/	YES	/	YES	/	YES	/	YES
Founding year FE	/	YES	/	YES	/	YES	/	YES	/	YES
Observations	2294	2259	2846	2758	7912	7763	1867	1809	2820	2768
Groups (Firms)	938	920	915	886	2734	2679	692	672	1391	1367
R^2	0.1343	0.1704	0.1433	0.1716	0.0404	0.0799	0.1135	0.1577	0.0503	0.0820

Note: The time-invariant variables for the POLS specifications are not shown in this table. Standard errors in parentheses. Standard errors clustered by firm. Stars indicate significance levels: * p<0.1, ** p<0.05,*** p<0.01.

2.4.3.2 VC investor type

Table 2.7 separates the outcome variable into investments by business angels (*BA*), corporate VC (*CVC*), and independent VC (*IVC*). In the fixed effects models (1), (3), and (5), the coefficient of *Public Support* is significant and positive for all VC sources but is the largest for business angels (4.8%, $p < 0.01$), followed by independent VCs (3.7%, $p < 0.01$), and lastly by corporate VCs (2.3%, $p < 0.01$). For the coefficient of *Public Support x Academic*, the order of magnitude holds with a greater chance for academic startups to obtain additional investment from business angels after receiving public support of 8.9% ($p < 0.01$), by independent VCs of 5.8% ($p < 0.05$), and, to lower significance, for corporate VCs with 3.2% ($p < 0.10$). These results are robust in the POLS specification in columns (2), (4), and (6). Therefore, we confirm hypotheses H3a and H3b.[13]

Table 2.7: Results by investor type

	BA		CVC		IVC	
	(1) FE	(2) POLS	(3) FE	(4) POLS	(5) FE	(6) POLS
Public Support	0.0475***	0.0291***	0.0226***	0.0112***	0.0365***	0.0273***
	(0.0133)	(0.0082)	(0.0081)	(0.0038)	(0.0114)	(0.0057)
Public Support x Academic	0.0889***	0.0677***	0.0324*	0.0381***	0.0573**	0.0578***
	(0.0289)	(0.0177)	(0.0192)	(0.0096)	(0.0235)	(0.0143)
Academic		-0.0088		-0.0074***		-0.0070*
		(0.0077)		(0.0020)		(0.0039)
Export	0.0205***	0.0119*	0.0147***	-0.0002	0.0195***	-0.0003
	(0.0057)	(0.0072)	(0.0043)	(0.0033)	(0.0044)	(0.0041)
Market Novelty	0.0196***	0.0277***	0.0083***	0.0086***	0.0093***	0.0157***
	(0.0041)	(0.0067)	(0.0026)	(0.0033)	(0.0034)	(0.0042)
1-10 full-time employees	0.0038	0.0335***	0.0039	0.0100***	0.0068*	0.0146***
	(0.0048)	(0.0057)	(0.0027)	(0.0023)	(0.0040)	(0.0032)
>10 full-time employees	-0.0200**	0.0191*	0.0019	0.0100**	0.0045	0.0284***
	(0.0089)	(0.0104)	(0.0050)	(0.0044)	(0.0081)	(0.0081)
Firm FE	YES	/	YES	/	YES	/
Time FE	YES	YES	YES	YES	YES	YES
Industry FE	/	YES	/	YES	/	YES
Founding year FE	/	YES	/	YES	/	YES
Observations	17739	17357	17739	17357	17739	17357
Groups (Firms)	6670	6524	6670	6524	6670	6524
R^2	0.0668	0.0870	0.0304	0.0447	0.0468	0.0868

Note: The time-invariant variables for the POLS specifications are not shown in this table. Standard errors in parentheses. Standard errors clustered by firm. Stars indicate significance levels: * p<0.1, ** p<0.05, *** p<0.01.

[13] To compare effect sizes across investor types, we should also compare the increase in probability relative to the baseline probability (of non-academic startups) of receiving investment from that type of investor. We find that startups experience a larger relative increase for CVCs (177%) and IVCs (148%) after attracting public support than for BAs (72%). Similarly, the additional effect for academic startups represents a larger relative increase for IVCs (232%) than for BAs (133%).

2.4.4 Analysis of time persistency

To test for the time persistency of the main effect, Table 2.8 lagged and forwarded key variables.[14] Models (1) and (2) present an FE and a POLS specification with one lag, models (3) and (4) include one lag and one forward, and models (5) and (6) include two lags. Including more lags and forwards would be desirable, but is infeasible as the sample becomes too constrained when multiple lags are included. Because of these constraints, with the sample already becoming borderline too small with two lags, we use the one-lag model to test hypothesis H4b, namely, whether the effect is more persistent for academic startups. We use the two-lag model to test hypothesis H4a, namely, whether the effect is time-limited.

First, we find support for hypothesis H4b in the one-lag model presented in columns (1) and (2). Across specifications, we find that the coefficient of *Public Support x Academic* is consistently significant and positive, implying that the probability that an academic startup receives VC increased in the year in which it attracts public support but also in the year afterward. Columns (3) and (4) present a sanity check for our specification: by including a forward term, it allows the possibility that the probability of VC increases *before* public support was attracted. If this coefficient were significant, it would invalidate the signaling mechanism. The results show that this is not the case.

The persistent lagged effect is only present for academic startups. For startups in general, the coefficient of $Public\ Support_{t-1}$ is statistically insignificant. The coefficient of *Public Support* turns insignificant for the FE specification and is considerably smaller than the coefficients estimated in the benchmark model. This is consistent with the interpretation that the (joint) probability of receiving VC grows when the startup receives public support, but the probability of receiving public support in a particular year remains low.

Columns (5) and (6) include a second lag to test for the time-limited nature of signals posited in hypothesis H2a. Considering that we only find a time-persistent effect for academic startups, we focus on the coefficients of *Public Support x Academic*. The coefficient is positive and significant in year t. In year $t-1$, it turns insignificant but remains positive.[15] In year $t-2$, however, the coefficient drops to close

[14] Note that public support and private VC are coded differently here. The investment variables are recoded as 0 in the years they did not receive the investment and 1 in the year they received the investment. This allows us to pin down the exact timing of the effect.

[15] Note that we do not interpret this lack of statistical significance as meaningful, considering the smaller sample and the inefficiencies introduced by the highly correlated lag structure. Rather, we interpret mainly the coefficient sizes in this specification.

Table 2.8: Analysis of time persistency

	Private VC					
	1 lag				2 lags	
	(1) FE	(2) POLS	(3) FE	(4) POLS	(5) FE	(6) POLS
Public Support	0.0038	0.0248***	0.0045	0.0231**	-0.0057	0.0321**
	(0.0105)	(0.0095)	(0.0101)	(0.0095)	(0.0147)	(0.0135)
Public Support$_{t-1}$	0.0033	0.0056	0.0039	0.0050	0.0110	0.0134
	(0.0072)	(0.0066)	(0.0073)	(0.0067)	(0.0102)	(0.0093)
Public Support$_{t-2}$					-0.0007	0.0068
					(0.0066)	(0.0063)
Public Support$_{t+1}$			0.0009	0.0161		
			(0.0180)	(0.0161)		
Public Support x Academic	0.0513**	0.0707***	0.0510**	0.0701***	0.0973***	0.0626**
	(0.0239)	(0.0217)	(0.0235)	(0.0217)	(0.0346)	(0.0312)
Public Support x Academic$_{t-1}$	0.0509***	0.0595***	0.0510**	0.0587***	0.0187	0.0333
	(0.0197)	(0.0176)	(0.0199)	(0.0178)	(0.0248)	(0.0215)
Public Support x Academic$_{t-2}$					0.0062	0.0050
					(0.0182)	(0.0142)
Public Support x Academic$_{t+1}$			-0.0057	-0.0114		
			(0.0299)	(0.0279)		
Academic		-0.0035		-0.0040		-0.0025
		(0.0035)		(0.0040)		(0.0036)
Market Novelty	0.0024	0.0121***	0.0035	0.0113**	0.0038	0.0090*
	(0.0060)	(0.0045)	(0.0065)	(0.0050)	(0.0069)	(0.0048)
Export	0.0048	-0.0066*	0.0105	-0.0055	0.0026	-0.0021
	(0.0067)	(0.0034)	(0.0077)	(0.0039)	(0.0077)	(0.0035)
1-10 full-time employees	0.0030	0.0076***	0.0045	0.0076**	0.0080	0.0043
	(0.0060)	(0.0029)	(0.0067)	(0.0033)	(0.0065)	(0.0029)
>10 full-time employees	-0.0220	0.0142**	-0.0171	0.0134*	0.0038	0.0194**
	(0.0152)	(0.0071)	(0.0168)	(0.0078)	(0.0199)	(0.0078)
Firm FE	YES	/	YES	/	YES	/
Time FE	YES	YES	YES	YES	YES	YES
Industry FE	/	YES	/	YES	/	YES
Founding year FE	/	YES	/	YES	/	YES
Observations	13147	12859	10805	10577	9110	8900
Groups (Firms)	5237	5121	4200	4114	3747	3659
R^2	0.0232	0.0595	0.0244	0.0646	0.0316	0.0556

Note: The time-invariant variables for the POLS specifications are not shown in this table. Standard errors in parentheses. Standard errors clustered by firm. Stars indicate significance levels: * p<0.1, ** p<0.05, *** p<0.01.

to zero. Hence, within the constraints of this exercise, we conclude that hypothesis H4a is supported and conclude that the effect of public support for attracting VC by academic startups is time-limited.

2.4.5 Probabilities of funding patterns

Finally, we present a synthesizing exercise to further contextualize and verify the results. Here, we use a multinomial logit model to estimate the probability that a startup achieves a certain funding *pattern*, namely, whether it, throughout the observation period, never attracts public support nor VC, whether it attracts only public support but no VC (or vice versa), whether it attracts public support and VC

in the same year, or whether it attracts public support before VC (or vice versa). We then compare differences in outcome probabilities between academic startups and others.[16]

The results are presented in Table 2.9. The full results are presented in Table A6 in the appendix. The first column displays the log odds of academic startups for a given funding category in relation to the baseline category, "No funding". For easier interpretation, the second column presents marginal effects that present the additional probability of academic startups achieving the outcome, compared to other startups, and column three presents the relative increase compared to the baseline probability for non-academic startups. The latter shows that, compared to the average non-academic startup, academic startups are 7% less likely to obtain neither public support nor private VC, 20% more likely to obtain public support but no private VC, 17% more likely to receive public support and private VC in the same year, and 48% more likely to receive public support in one year and private VC in a later year.

Table 2.9: Outcome probabilities for academic startups

Funding	Logg odds	Marginal effects	Relative increase
No funding	(base)	-0.0498***	-7.11%
		(0.0163)	
Only private VC	0.0261	-0.0015	
	(0.1539)	(0.0053)	
Private VC first, then public support	0.3929	0.0005	
	(0.3014)	(0.0004)	
Only public support	0.2531***	0.0410***	20.35%
	(0.0974)	(0.0157)	
Public support first, then private VC	1.0665***	0.0068***	48.38%
	(0.2163)	(0.0013)	
Private VC and public support in the same year	0.7924***	0.0030***	17.44%
	(0.2036)	(0.0008)	

Note: N= 6536. The log odds and marginal effects are displayed for the coefficient of *Academic*. For the multinomial log-odds results, the time-invariant control variables are not shown in this table; the full version can be found as table A6 in the appendix. The "relative decrease/increase" is only shown in case the probability of the funding type is significantly different between the academic and non-academic startups. It represents the relative difference in probabilities and is calculated by the division of the marginal effects coefficient by the mean of non-academic startups for a given funding outcome. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Thus, academic startups are more likely to receive public support, which could suggest that the public support's effect on private VC investment is due to selection bias. However, the results challenge this assumption. If selection were the sole driver, the effects across different funding sequences, including public support, would be similar, but they are not. The stronger effect of obtaining public support

[16] To account for unobserved heterogeneity, use the entropy balancing weights used in subsection 2.4.2.

a year before private VC (48%) in comparison to only receiving public support and no private VC (20%) further suggests that the timing and signaling value of public support, rather than selection alone, drive follow-on VC investment.

2.5 DISCUSSION AND CONCLUSION

In this paper, we argue that signals stemming from public support are different for academic startups because of their unique characteristics and the specific uncertainties that these characteristics carry toward VCs. These uncertainties relate to the inherent technological complexity of academic startups (Pahnke et al., 2015), typically lower maturity (e.g., Fini et al., 2023), the commitment of academic entrepreneurs towards their startups (Fini et al., 2022; Rasmussen and Sørheim, 2012), and the suitability of academic entrepreneurs towards leading and growing a business (Gubitta et al., 2016; Mathisen and Rasmussen, 2019; Wright et al., 2006). We hypothesize that, despite concerns about the government as credible certifier (Colombo et al., 2016), public support signals are more effective signals for academic startups because of the higher ability of the evaluating bodies to evaluate technological potential (Pahnke et al., 2015; Toole and Czarnitzki, 2007), the potentially more important role of activating signals in overcoming barriers due to maturity (Bianchi et al., 2019), and the commitment signal of attracting public support, which is more critical for academic founders (Busenitz et al., 2005; Prasad et al., 2001).

Building on detailed information on startups in Germany, our results confirm that attracting public support increases the probability of obtaining VC investments more for academic startups than for others. In addition, we show that this effect is strongest in high-tech manufacturing (also referred to as *deep-tech*) startups, which are the most complex and uncertain in terms of technology and risk (Kask and Linton, 2023; Nedayvoda et al., 2021; Tech, 2018). For other startups, we find the strongest effects in software and knowledge-intensive service industries – in line with the idea that investors have different concerns when investing in academic startups compared to other startups. We also show that the effect is strongest towards Business Angels, in line with prior research on startups in general (Berger and Hottenrott, 2021) and in line with the notion of differential screening capacities across inventor types (Fiet, 1995; Maxwell et al., 2011; Van Osnabrugge, 2000). Furthermore, we show that the effect is short-term, i.e., it persists only for one year after funding, hinting at both the diminishing value of signals in dynamic environments

(Feldman and Kelley, 2003) and the potentially more persistent information value of commitment signals in the context of academic startups (Busenitz et al., 2005; Prasad et al., 2001). Finally, we show that, although academics might be better at writing grant applications and thus may self-select into public support funding (Toole and Czarnitzki, 2007), this is not the sole driver of the effect, and a greater part could be attributed to a signaling value.

Our study makes several contributions to rethinking academic entrepreneurship by providing new insights into the indirect effects of policy initiatives for fostering academic startups and by highlighting policy implications of efforts for promoting academic entrepreneurship. In particular, we first contribute to the literature on the follow-on effects of public support on VC investment by extending these insights to the context of academic startups. Extant literature has either focused on signaling effects by the academic qualities of startups (Hsu, 2007), or on the different context of IPO valuation (Bonardo et al., 2011; Colombo et al., 2019). The few existing studies addressing the relation between public support and follow-on finance for academic startups are limited, as they focus on cohorts of academic startups (Fini et al., 2023; Gubitta et al., 2016) or within publicly supported firms (Toole and Czarnitzki, 2007). In doing so, these studies inform about the existence of a signal also for academic startups but are unable to provide further insights on the differences to non-academic ones. In comparison to these studies, our study provides a comparison of VC investment before and after public support for both academic and non-academic startups, allowing us to draw the conclusion that the effect is, in fact, stronger for academic startups.

Second, we contribute to the theoretical understanding of the potential mechanisms driving signaling effects specifically for academic startups. Despite the policy attention aimed at fostering academic entrepreneurship (Ayoub et al., 2017; Lehmann et al., 2024; Rasmussen and Sørheim, 2012; Sandström et al., 2018; Toole and Czarnitzki, 2007), the importance of the provision of equity finance for high-tech startups (e.g. Bertoni et al., 2011; Grilli and Murtinu, 2014), and the higher perceived funding risks associated with academic startups (Mathisen and Rasmussen, 2019; Roche et al., 2020), previous literature has not paid much attention to understanding signaling effects specifically for academic startups. While we cannot offer empirical confirmation of these micro-mechanisms, our study adds to the debate by theorizing on the differential importance of pointing signals, activating signals (Bianchi et al., 2019), and commitment signals (Busenitz et al., 2005; Prasad et al., 2001) in the context of academic entrepreneurship, as well as on the potentially dif-

ferent dynamics vis-a-vis funding body expertise for academic startups (Colombo et al., 2016; Lerner, 1999, 2002; Toole and Czarnitzki, 2007).

Finally, we contribute to understanding the role of signals for academic startups in Europe. Despite initial lower levels of venture capital compared to the U.S., the European venture capital market has become essential in providing financing opportunities for new ventures and is experiencing remarkable growth (Berger and Hottenrott, 2021; Caselli and Zava, 2023; OECD, 2011). Yet, most existing literature on the topic is conducted in the U.S. context (Fini et al., 2023; Gubitta et al., 2016; Guerrero and Urbano, 2019; Toole and Czarnitzki, 2007). We conduct our study in the context of Germany, a country with a strongly developed academic science, where academic entrepreneurship is increasingly encouraged, and promoting academic entrepreneurship has been a policy priority (Lehmann et al., 2024).

Our results have implications for policymakers and founders. First, policymakers might underestimate the impact of policy programs for academic entrepreneurs (Ayoub et al., 2017; Rasmussen et al., 2011; Sandström et al., 2018; Toole and Czarnitzki, 2007) when they do not take the impact on follow-on investing into account. Second, actors and institutions fostering to strengthen the growth of academic startups, such as support programs and university-linked accelerators, should incorporate the higher impact of achieving public support on follow-on finance in their strategies. For instance, by offering support for attracting public support for academic founders. Lastly, our results provide opportunities for founders of academic startups to increase their probability of receiving venture capital investments by attracting public support for their ventures first.

Our analysis faces several limitations that might offer opportunities for follow-up research. Most importantly, we must acknowledge that while we offer an advance in theory on the mechanisms driving signals for academic startups and the potentially most salient nature of these signals, we cannot empirically delineate them. Future research might design ways to disentangle and understand these mechanisms by exploiting heterogeneity between government support programs. This could be done by focusing on, for instance, the importance of program prestige and credibility (Colombo et al., 2016), programs with higher and lower potential to reduce technological uncertainty (Lerner, 1999, 2002; Pahnke et al., 2015), programs with higher or lower activating properties because of the nature or volume of the support (Bianchi et al., 2019), or programs with higher or lower application burdens, which might signal differential degrees of commitment (Busenitz et al., 2005; Prasad et al., 2001). Each of these, requiring detailed information on specific programs and

therefore outside of the scope of our current approach, would contribute to a deeper understanding of the mechanisms through which the signal value of public support manifests. Related to this, our study would have benefited from more detailed information on investment volumes and timing for both public grants and VC. We encourage further research collecting and exploiting more fine-grained information to further disentangle the micro-mechanisms behind signaling effects. Finally, future research could attempt to incorporate potential third-degree effects, that is to say, the impact that achieving public support has on the development of the venture's funding path, also taking into account that achieving certain types of support might reduce future funding needs. Such insights could help to further advance the understanding and conceptualization of different types of academic start-ups and the possible variation in the direct and indirect effectiveness of policy tools to promote them.

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Chapter 3

The Academic Startup Advantage: Research Output or Human Capital?[1]

Academic startups play a crucial role in innovation and economic growth, yet they vary significantly in their reliance on research outputs versus broader scientific skills. This study moves beyond the prevailing approaches of either broadly generalizing all academic startups or narrowly focusing on those that commercialize research results. Instead, we introduce a continuous measure of research-basedness, categorized into four levels. Using data from the IAB/ZEW Startup Panel, we analyze how varying degrees of academic startups' research-basedness influence innovation and sales performance. Our findings reveal that highly research-intensive academic startups excel in R&D and radical innovation but face initial commercialization challenges, while limited research-based academic startups still achieve notable market novelty. These insights contribute to academic entrepreneurship literature and inform policy by emphasizing the need for tailored support strategies, balancing technological advancements with market application to maximize the impact of academic entrepreneurship in different contexts.

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3.1 INTRODUCTION

A long literature investigates academic start-ups and academic entrepreneurs (Link et al., 2015; Rothaermel et al., 2007). Academic start-ups contribute especially to economic development and job creation through their focus on innovation and technology development (Botelho et al., 2021; Shane, 2004), and, through their ability to tap into cutting-edge research, form especially high-potential forms of entrepreneurship (Tartari and Stern, 2021). While the existing literature clearly demonstrates the importance and success of academic entrepreneurs, there is less clarity regarding how 'academic startups' are defined and the implications of this ambiguity. A major stream in the literature implicitly focuses on academic startups founded with the intent to commercialize scientific or technological research results (e.g., Agarwal and Shah, 2014; Shane, 2004). A second stream acknowledges that academics might also start ventures that do not serve directly to commercialize research, but rather utilize the scientists' skills and experiences to capitalize on other market opportunities (e.g., Goel and Grimpe, 2012; Hindle and Yencken, 2004; Pirnay et al., 2003).

Despite growing interest, the literature has yet to systematically differentiate between academic startups that rely on specific research outputs and those that leverage general academic skills and tacit human capital. As Coad et al. (2021) note "detecting whether university start-up entrepreneurs actually draw on knowledge developed at the university remains a difficult challenge for spinoff research." (p.3). This ambiguity has led to an overgeneralization of academic entrepreneurship, obscuring important differences in the drivers and outcomes between different categories of academic startups. Initial evidence indicates that academic startups are not homogeneous (Czarnitzki et al., 2014; Goel and Grimpe, 2012), highlighting the need for an in-depth analysis to identify the different types of academic startups and how they uniquely contribute to innovation and economic growth. By generalizing academic startups, we might be overestimating the spillovers from research-related knowledge and underestimating those from soft skills, such as a scientific approach to problem-solving (Camuffo et al., 2020). In essence, the overarching question is: Does the competitive advantage of academic startups stem from actual research outputs or from the broader skills and human capital that academics acquire?

In this paper, we aim to fill this gap through two main contributions. First, we shed light on the various definitions and criteria used to define academic startups (e.g., Agarwal and Shah, 2014; Fini et al., 2011), and show that the perspectives of

academic entrepreneurs whose ventures are not directly based on research results are largely lacking. Second, we investigate the relation between, on the one hand, the degree to which academic startups are based on research and, on the other, the startup's success in terms of innovation and growth. Starting from the academic entrepreneurship and tacit knowledge literature, we introduce a new perspective by bringing in human capital (HC) theory (Becker, 1964; Unger et al., 2011) to explain why performance differences might exist across the research-basedness of academic startups. High-research-based academic startups possess superior task-specific technological human capital from frontier research, enabling radical innovation (Marvel and Lumpkin, 2007; Stephan, 2014), but they often lack market knowledge and managerial skills, limiting early sales performance (Colombo and Piva, 2008; Gourville, 2005; Gubitta et al., 2016). In contrast, lower research-based academic startups, while less likely to commercialize radical technologies, benefit from broader general human capital, greater cognitive flexibility, and often more industry or consulting experience, which enhances market-related skills and early sales performance (Goel and Grimpe, 2012; Nagle and Teodoridis, 2020; Wennberg et al., 2011).

Thus starting from a general academic startup definition (e.g., Breschi et al., 2021; Coad et al., 2021; Colombo and Piva, 2008), "at least one of the founders has worked/works at a university or research institution", following Dorner et al. (2017), we find support for these HC theories using the IAB/ZEW Startup Panel survey data on academic startups, which allows us to come to a more nuanced notion of 'research-basedness', and to benchmark the performance, in terms of innovation and sales, of academic startups with varying degrees of research-basedness to that of non-academic startups. Thereby allowing for a better understanding of the boundary conditions of the high potential of academic entrepreneurship.

Our findings reveal that academic entrepreneurship is far from homogeneous. Instead of a simple dichotomy between research-based and non-research-based startups, our analysis identifies a spectrum of research-basedness. Startups in the highest quartile of research intensity exhibit superior R&D investments and generate more radical innovations, both at the market and global levels, though they experience a significant lag in sales performance that only catches up after five years (Löfsten and Lindelöf, 2005; Mathisen and Rasmussen, 2019; Shane, 2004; Tartari and Stern, 2021). Conversely, startups with limited research-basedness, while investing less in R&D, still achieve, to a lower extent, notable market novelty, suggesting that even limited application of scientific capabilities and experience can enhance opportunity recognition (Criaco et al., 2014; Ronstadt, 1988). Additionally, the ob-

served inefficiency in high-mid-tier research-based startups indicates that a partial commitment to leveraging research expertise may not yield proportional innovation outcomes, underscoring the distinct roles of specific versus general human capital (Ganotakis, 2012; Wright et al., 2006).

This differentiation is not merely academic, it has important implications for both entrepreneurship research and policy design. Prior studies have struggled to reconcile inconsistent performance outcomes among academic startups (Czarnitzki et al., 2014; Wennberg et al., 2011), partly because they have overlooked the heterogeneity in how these ventures draw on research outputs versus general scientific competencies (Coad et al., 2021; Goel and Grimpe, 2012). Without understanding these differences, policymakers and support organizations risk applying undifferentiated or misaligned interventions. For instance, while research-intensive startups may benefit most from technology transfer support, mentorship, management skills, and market access initiatives (Agarwal and Shah, 2014; Colombo and Piva, 2008), ventures leveraging broader scientific skills may require programs focused on opportunity recognition, entrepreneurial training, and network development (Camuffo et al., 2020; Criaco et al., 2014). Our findings clarify this distinction by demonstrating that startups with varying degrees of research-basedness exhibit systematically different innovation and growth patterns (Löfsten and Lindelöf, 2005; Mathisen and Rasmussen, 2019; Shane, 2004; Tartari and Stern, 2021). This insight not only helps explain conflicting results in prior research but also provides a necessary foundation for designing tailored support policies and incubation programs that align with each startup's unique capabilities and development trajectory (Colombo and Piva, 2008; Goel and Grimpe, 2012). Ultimately, knowing *how* academic startups differ is essential for knowing *how to correctly support them*, whether the goal is to maximize technological breakthroughs or foster broad-based economic and societal impact.

3.2 THEORY DEVELOPMENT

3.2.1 Definition of academic startups

The interpretation and definition of academic startups have been subject to ambiguity within the literature, leading to various explanations and contradictions. Terms like "university spin-offs" (e.g., Fini et al., 2023; Löfsten and Lindelöf, 2005; Pirnay et al., 2003), "academic spin-offs" (e.g., Clarysse et al., 2007; Fini et al., 2011), "university spinouts" (e.g., Wright et al., 2006), "academic startups" (e.g., Colombo

and Piva, 2012), "university startups" (e.g., Coad et al., 2021), and "research-driven spin-offs" (e.g., Conceição et al., 2012) have been interchangeably used.

Several researchers have attempted to clarify the overarching dimensions and characteristics of the used definition (Mathisen and Rasmussen, 2019; Pirnay et al., 2003). The first steps were taken by Pirnay et al. (2003), who discovered two overarching dimensions: (1) the status of the founders and (2) the nature of the knowledge transferred. Mathisen and Rasmussen (2019) reintroduce these dimensions as (1) entrepreneurs and (2) forms of knowledge, while adding two new dimensions, (3) institutional origin and (4) sponsorship. First, the status of the founders concerns the background of the entrepreneurs. The most prevalent distinction concerns the extensive research experience acquired, ranging from researchers to staff members to students with limited exposure to in-depth research (Pirnay et al., 2003). Additionally, academics might be expected to work full-time in the startup, while some definitions allow being partially employed by the university/research institution. Second, the nature of the knowledge distinguishes between explicit and tacit knowledge. Explicit knowledge is easier to transfer and might be protected by legal instruments (e.g., patents). However, often the knowledge is tacit, embodied within the individual, and implies interactive learning and cooperation to be accessed. Third, institutional origin specifies where the knowledge is developed at a university, public research institute, or governmental lab (Mathisen and Rasmussen, 2019). Lastly, the sponsorship refers to startups receiving support from the parent institution or a technology transfer office (TTO), or that they were independently founded.

The main focus of the definition is often fixed on the knowledge transfer dimension. According to Agarwal and Shah (2014), "academic entrepreneurship (also referred to as university spin-offs or academic spinouts) is defined as new venture formation by faculty, staff or students who innovate in an academic or non-profit research context, and subsequently found a firm that directly exploits this knowledge" (p.114). They refer to Shane's (2004) proposition that academic entrepreneurship requires a direct knowledge transfer link between the university and the startup, which can be interpreted as a stricter requirement on the type of knowledge. Similarly, Mathisen and Rasmussen (2019) does not specify criteria regarding sponsorship, institution, and entrepreneur, but does require a university spin-off (USO) to commercialize research results and scientific knowledge. Link et al. (2015) argue that "academic entrepreneurship, at its most basic level, involves the spillover of research knowledge into commercialized goods and services" (p.247). Offering more

flexibility regarding the type of knowledge transferred, Pirnay et al. (2003) argue that tacit knowledge can take various forms such as capabilities, expertise, and experience. They define university spin-offs (USOs) as "new firms created to exploit commercially some knowledge, technology or research results developed within a university" (Pirnay et al., 2003, p.356). On the other side, certain researchers do not require a knowledge transfer to be considered an academic startup, they emphasize the founders. Fini et al. (2011) describe "an academic spin-off as a company that has either a university or at least one academic (full, associate, or assistant professor; or Ph.D. candidate, research fellow, or technician) among the founders, regardless of the presence of a formal commitment from the parent university" (p.1117). Likewise, Coad et al. (2021) define university startup entrepreneurs "as persons who are employed at a university in year t and work in a new firm in year t+1" (p. 2), forgoing any mention of knowledge transfer.

Thus, following these definitions and different views, there are two large strands within the academic entrepreneurship literature: academic startups and academic spin-offs. First, a broader, inclusive definition is applied in which the main requirement is that an academic is part of the founding team. These can be referred to as (general) "academic startups (ASUs)" or "university startup entrepreneurs (USEs)" (e.g., Breschi et al., 2021; Coad et al., 2021; Colombo and Piva, 2008; Roche et al., 2020). It does not require a specific knowledge transfer and allows academics to start a new venture based on unrelated knowledge. A subgroup of these academic startups is the "academic spin-offs" (ASOs) or "university spin-offs" (USOs) (e.g., Abootorabi et al., 2021; Agarwal and Shah, 2014; Iacobucci et al., 2011; Link et al., 2015; Mathisen and Rasmussen, 2019; Zellmer-Bruhn et al., 2021). They require a knowledge transfer from the university to the startup and might be sponsored by the parent institution or a technology transfer office (TTO). However, it remains unclear where to draw the line on what knowledge transfer may entail. Depending on the exact definition described, the nature of the knowledge might vary from very restricted codified knowledge (e.g., IP) to broader scientific capabilities. Nevertheless, the "spin-off" term in the literature should always be carefully interpreted as the term is sometimes loosely used and might refer to academic startups rather than spin-offs as defined above (e.g., Fini et al., 2011). Additionally, academic spin-offs should contain a knowledge transfer, however, in some situations, it is unclear whether this information or new technology comes from the academic founder or other co-founders.

For the purpose of this research, academic startups are taken into account un-

der the definition: "at least one of the founders needs to have worked/works at a university or other research institution. Jobs as a teaching assistant, research assistant, and internships or similar do not count." It opts for a broader perspective of academic entrepreneurship and allows for a detailed perspective on often overlooked academic startups that do not transfer specific research results, methods, or skills. Concerning the dimensions of Pirnay et al. (2003) and those of Mathisen and Rasmussen (2019), this paper thus only establishes criteria within the founder dimension.

3.2.2 Types of knowledge transfer

As previously mentioned, the knowledge transfer component of academic entrepreneurship is often regarded as the exploitation of research results or scientific knowledge in a new venture. This knowledge can be codified or tacit. In a strict sense, it is intellectual property from which new technologies arise that could be codified and possibly legally protected by patents (Mathisen and Rasmussen, 2019; Wright et al., 2006). In a broader perspective, tacit knowledge is the scientist's technological understanding of the development of a particular new knowledge or technology in the context of commercialization (Hindle and Yencken, 2004; Karnani, 2013; Zellmer-Bruhn et al., 2021). In this literature, knowledge and technology transfer are often interchangeably used as synonyms (Dorner et al., 2017; Karnani, 2013).

However, some researchers have recognized that tacit knowledge goes beyond the research results and technological components (Hindle and Yencken, 2004; Pirnay et al., 2003). Dorner et al. (2017) analyze the specific skills, methods, and results acquired during the scientist's research career. They specify two types of spin-offs: transfer and competence spin-offs. A transfer spin-off is quantified as a startup born from research results or new scientific methods, or techniques developed during the university career. While in a competence spin-off, specific research-based skills acquired are essential for the founding of the new venture. Despite the indirect influence, these companies are still acknowledged for transferring research-related knowledge to a lesser extent. Taking a step further, this embodied tacit knowledge can take multiple forms such as capabilities, expertise, and experiences (Pirnay et al., 2003). These stem from the individual's personal knowledge accumulated during their scientific career. In contrast to Dorner et al. (2017), the acquired skills are not required to be closely linked to the research and could be general capabilities. Finally, Hindle and Yencken (2004) define under tacit knowledge (1) the ability to

find ideas that can be converted into opportunities and (2) the technology and scientific background of the original investors.

These traits, abilities, and scientific background can be perceived as the human capital of the scientific founders. When shifting the literature focus from a knowledge transfer perspective to a human capital context, the main principles stay the same. Academics possess human capital specific to their academic experiences, but are not limited to research or technology-related knowledge. Criaco et al. (2014) argue the existence of university human capital, which is linked to a researcher's knowledge and experience due to their academic career. Similarly, Colombo and Piva (2012) argue that the genetic characteristics of academics are different from non-academics. The human capital of the academic founders, their skills and knowledge, is transferred to the new venture, where they form the basis for the firm's competency endowment (Colombo and Grilli, 2010; Colombo and Piva, 2012), which aligns with the tacit knowledge transfer view. An example of such tacit knowledge is the scientific mindset, which can be considered a skill all academics acquire (Coad et al., 2021; Roche et al., 2020), as they receive substantial technical training and develop scientific problem-solving practices (Roche et al., 2020). The scientific mindset allows academics to develop a framework and theories that can be tested with hypotheses to solve problems (Camuffo et al., 2020; Coad et al., 2021; Nightingale, 2014; Roche et al., 2020). It structures the way of thinking, leading to better-informed decisions and thus improving entrepreneurial decision-making (Camuffo et al., 2020).

Although the existence of a general academic human capital aspect to entrepreneurship is acknowledged (Criaco et al., 2014), and general academic skills and capabilities are considered tacit knowledge (e.g., Hindle and Yencken, 2004; Pirnay et al., 2003), the literature fails to recognize the startups that mainly focus on these types of knowledge transfers, and has not yet investigated specifically the contributions of academic entrepreneurs that do not rely on research results. Some authors have acknowledged the non-research academics. Goel and Grimpe (2012) highlight their drivers into entrepreneurship, while Czarnitzki et al. (2014) contribute by exploring the divergence in employment growth between non-research and research-based academics. They urge further exploration into the concept of non-research-based academics and their performance. Similarly, Boudou and Roche (2025) urge a shift from a binary perspective to exploring the degree of specialized scientific expertise embedded in science-based startups. While Zellmer-Bruhn et al. (2021) mainly focus on academic spin-offs, they stress the need to pay more atten-

tion to "non-traditional" academic startups and advocate for a broader perspective on academic entrepreneurship that moves beyond the traditional model of science-based ventures supported by university technology transfer offices (TTOs).

3.2.3 Performance: innovation & growth

3.2.3.1 Innovation

Concerning innovation, research-based academic startups (closely related to the literature's strict sense of academic spin-offs) are inherently more innovative due to their cutting-edge research knowledge transfers from the university to the industry (Löfsten and Lindelöf, 2005; Mathisen and Rasmussen, 2019; Shane, 2004; Stephan, 2014; Tartari and Stern, 2021). The academics have developed a strong technical background and in-depth knowledge about the commercialized research results (Colombo and Piva, 2008). This is consistent with the earlier expectations that research-based academics are more likely to come from technological backgrounds (e.g., engineering) and concentrated within high-tech industries (Agarwal and Shah, 2014; Coad et al., 2021; Colombo and Piva, 2008; Goel and Grimpe, 2012; Tartari and Stern, 2021; Visintin and Pittino, 2014). Given a resource-based view, the key sustainable competitive advantage of the research-based academic startup is its technological competencies (Colombo and Piva, 2008; Löfsten and Lindelöf, 2005). Research-based startups are thus expected to put more effort into R&D (Löfsten and Lindelöf, 2005; Mathisen and Rasmussen, 2019). Although no difference between academic and non-academic startups can be found in the number of new products and processes, academic startups' product innovations are more radical (Gilsing et al., 2010; Löfsten and Lindelöf, 2005; Stephan, 2014).

To better understand which academic startups are more likely to be radically innovative, depending on their research-basedness, we draw on Human Capital theory. Human Capital theory distinguishes between general human capital and specific human capital. General human capital is not task-related or directly related to a specific job, i.e., education and general employment experience (Becker, 1964; Marvel and Lumpkin, 2007; Marvel et al., 2020; Rauch and Rijsdijk, 2013; Unger et al., 2011). In contrast, specific human capital is task-specific and related to a particular job, i.e., prior startup experience, entrepreneurial knowledge, industry-specific experience, management experience, knowledge of ways to serve the market, customer problems, markets, and specific technological knowledge (Brüderl et al., 1992; Marvel and Lumpkin, 2007; Marvel et al., 2020; Rauch and Rijsdijk, 2013; Unger et al.,

2011). General and specific HC have also been called, respectively, non-task-related and task-related HC (e.g., Marvel et al., 2016; Unger et al., 2011). As an example in the context of research-basedness, research results would be specific HC, while the scientific mindset is a general skill (Camuffo et al., 2020).

General HC is positively associated with radical innovation, especially formal education (Marvel and Lumpkin, 2007). Regarding specific HC, prior knowledge to serve the market appears to have a negative association with radical innovation, while technological knowledge has a positive influence. In other words, individuals with a limited understanding of ways to serve the market, but possessing advanced technological expertise, seem best suited to drive breakthrough innovations (Marvel and Lumpkin, 2007). High-research-based academics have the largest accumulation of applicable technological knowledge, as their cutting-edge research knowledge is transferred to the new venture as a competitive advantage. At the same time, due to an academic research career, academics have less market knowledge than non-academics (Colombo and Piva, 2012; Gubitta et al., 2016; Mathisen and Rasmussen, 2019; Wright et al., 2006). Similarly, lower-research-based academic startups have high general HC in the form of education and general research work experience with limited market-related knowledge. However, as they do not directly use their research-related results, methods, or skills in their new ventures, they are expected to have less task-specific applicable technological knowledge than high-research-based academics. Thus, given the high general HC of high-research-based academic startups in the form of formal education and high task-related technological skills, while having little knowledge about the market and how to serve the market, they are expected to be most likely to introduce radical innovation in technological breakthrough fields. Thus, expecting:

Hypothesis H1a *Academic startups scoring high on research-basedness are more likely to introduce radical innovations compared to non-academic startups.*

Hypothesis H1b *Academic startups scoring high on research-basedness are more likely to introduce radical innovations compared to academic startups scoring low on research-basedness.*

Although non-research-based academics do not directly apply their specific research findings, methods, or skills in their new ventures, they are nonetheless embedded in a highly technological, knowledge-intensive environment oriented toward

innovation and discovery. Knowledge emerges from an individual's unique life experiences, and this personal endowment can enable them to identify entrepreneurial opportunities that others may overlook (Ronstadt, 1988). Higher levels of human capital further increase the likelihood of opportunity recognition (Davidsson and Honig, 2003). In contrast to their research-intensive peers, low-research-based academic entrepreneurs may avoid the "tunnel vision" that often stems from deep specialization. This cognitive flexibility, combined with a diversified knowledge base developed within the academic environment, may enhance their capacity to engage with distant and novel knowledge domains (Nagle and Teodoridis, 2020), thereby increasing the potential for high-impact idea generation. Moreover, academics who cultivate business knowledge alongside scientific expertise tend to build stronger social capital and network connections (Mosey and Wright, 2007). These ties can broaden their "knowledge corridor" and improve their capacity for opportunity recognition (Marvel et al., 2020). Since researchers acquire university-specific knowledge and experience due to their academic career (Criaco et al., 2014), and that universities themselves are hubs of advanced technology and cutting-edge knowledge development, low-research-based academics may be particularly well positioned to recognize radical innovation opportunities, more so than non-academics. As a result, we hypothesize the following:

Hypothesis H1c *Academic startups scoring low on research-basedness are more likely to introduce radical innovations compared to non-academic startups.*

3.2.3.2 Sales Performance

Firm performance in academic startups is typically measured by sales growth (Clarysse et al., 2011; Helm et al., 2018; Hossinger et al., 2020; van Geenhuizen and Soetanto, 2013; Visintin and Pittino, 2014; Yagüe-Perales and March-Chordà, 2012; Zhang, 2009), but inconsistent findings across studies, partly due to differing definitions of academic startups, suggest that variations in research-basedness may influence performance outcomes (Ensley and Hmieleski, 2005; Mathisen and Rasmussen, 2019; Wennberg et al., 2011; Yagüe-Perales and March-Chordà, 2012).

Research-based academic startups often focus on cutting-edge technologies, giving them an edge in innovation. However, this strength comes with challenges, such as longer development timelines (Nedayvoda et al., 2021) and difficulties in marketing these innovations effectively (Gourville, 2005). Scientists may overestimate the value of their innovations, while consumers tend to undervalue the novelty of

new products (Gourville, 2005). However, the key performance barrier for research-intensive academic startups is their lack of managerial skills (Clarysse and Moray, 2004; Gubitta et al., 2016; van Geenhuizen and Soetanto, 2009; Wennberg et al., 2011; Wright et al., 2006). Specific human capital characteristics, particularly commercial and managerial experience, drive the positive influence of HC on growth (Colombo et al., 2004; Ganotakis, 2012).

Although all academic startups generally lack managerial expertise due to their academic training (Colombo and Piva, 2008; Gubitta et al., 2016; Wennberg et al., 2011; Wright et al., 2006; Yagüe-Perales and March-Chordà, 2012), variations may exist depending on the extent to which their ventures are research-driven. Ganotakis (2012) highlights an inverted U-shaped relationship between human capital and firm performance, suggesting that experienced founders may become overconfident in their skills, which may prevent them from seeking information that improves decision-making. Academics who commercialize their research results often possess deep expertise in their technologies, making them more prone to overconfidence and the neglect of managerial skills. In combination with their scientific focus, this tendency may lead them to focus primarily on technical challenges, overlooking business needs (West III and Noel, 2009). This is in line with the notion of the dark side of human capital, too much focus on specific HC can restrict the knowledge corridor and negatively affect the acquisition and search for relevant knowledge that is not directly related to the current (technological) knowledge base (Marvel et al., 2020). Conversely, academics whose startups are not based on their research may be less overconfident and more aware of their managerial limitations, prompting them to seek solutions for these challenges.

A larger number of non-research-based academic startups are driven into entrepreneurship due to spending more time on consulting projects for the industry in comparison to research-based academics (Goel and Grimpe, 2012). This suggests that non-research-based academic startups may spend more time on industry consulting, suggesting that these academics are more likely to acquire managerial experience before founding their ventures. Managerial experience, often gained in commercial settings, enhances market-specific human capital (tacit knowledge), social capital, and network ties, which improve market-related skills (Mosey and Wright, 2007; Wennberg et al., 2011; Zellmer-Bruhn et al., 2021). Taken together, non-research-based academics are likely to face fewer challenges from missing managerial skills compared to their research-intensive counterparts. van Geenhuizen and Soetanto's (2009) research confirms this view by showing that highly innova-

tive spinoffs, those introducing market or world-first innovations and spending at least 25% of turnover on R&D, face significantly larger obstacles to growth in the first years (<3 years) compared to low- to medium-innovative spinoffs, with the highest ranking obstacles being market-related, i.e., marketing knowledge and sales skills. However, these highly innovative research-based startups tend to catch up and overcome these challenges before their fifth year of founding, resulting in similar obstacle levels as low- to medium-innovative spinoffs. Therefore, we hypothesize:

Hypothesis H2a *Academic startups scoring high on research-basedness are more likely to have lower sales in the first years after foundation compared to non-academic startups.*

Hypothesis H2b *Academic startups scoring high on research-basedness are more likely to have lower sales in the first years after foundation compared to academic startups scoring low on research-basedness.*

3.3 DATA AND METHOD

3.3.1 Data

This study uses data from the 2007 to 2018 waves of the IAB/ZEW Startup Panel. The panel is based on a computer-assisted telephone survey conducted annually and coordinated by the Centre for European Economic Research (ZEW), covering approximately 5,000 to 6,000 startups each year. The sample is drawn using stratified random sampling from the population of all newly registered firms in Germany, excluding those in agriculture, mining, and the public sector. Participating firms can be followed for up to seven consecutive years. The first survey year provides rich information on the founding event and the characteristics of the founding team (e.g., academic entrepreneurship), while subsequent waves include data on innovation and other ongoing firm-level outcomes (Egeln et al., 2022). The final sample consists of 5,873 startups founded between 2007 and 2017, including 871 academic startups and 5,002 non-academic startups.

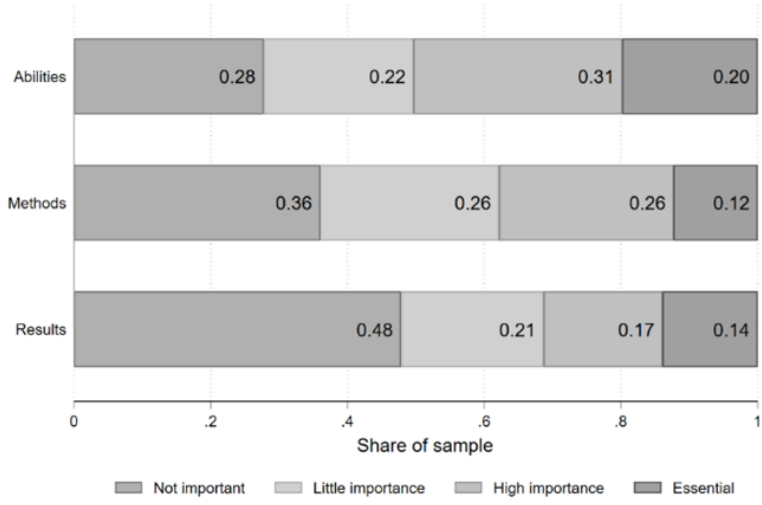
3.3.2 Variables

3.3.2.1 Type of (academic) entrepreneurs

Academic entrepreneurs can be identified in each wave through the question of whether any of the founders were (or are) employed at universities or research institutions.

Additionally, the survey asks about the importance of any abilities, new scientific methods or techniques, or own research results acquired by academic founders for the founding process of the company. Information on the importance of abilities, methods, and results is available for 871 respondents, and is measured on a 4-point scale ranging from not important to essential. Figure 1 displays the importance of each variable. While approximately three-quarters of respondents indicate that scientific abilities were at least a little important to the founding of the venture, and approximately two-thirds indicate that methods were at least a little important, only 52% of the sample indicates that concrete research results are at least a little important to the founding of the venture, and only one in seven respondents indicate that they were essential.

Figure 3.1: Summary statistics of the importance of abilities, methods, and results



Note: n = 871. Source: Authors' calculations based on IAB/ZEW Startup Panel wave 2013, 2014, 2015. Labels display percentages of respondents.

These variables thus allow distinction of research-based ventures, where results

matter strongly, from (non-)research-based ventures where scientific methods or abilities might still be important, from non-research-based ventures where even methods or abilities become less relevant. An exploratory factor analysis is applied to examine these dimensionalities of the research-based construct (see subsection 3.4.1). The results confirm that the three items are reflective of the same construct (Cronbach's alpha: 0.85). Therefore, we construct the startup's research-basedness as a summative scale based on the three items. In the extremes, the scale represents academic startups that do not use any research-related knowledge, and academic startups for which research is key in the creation of the venture.

To estimate the impact of research-basedness on the venture's innovation and sales, while still allowing for comparison to non-academic startups (which were not presented with these survey questions), we include the variable in the econometric analysis as a categorical variable, where the base level (0) reflects non-academic entrepreneurs, and the other levels the four quartiles of the continuous research-based academic startup variable. Then, it is possible to compare the outcomes for each quartile of research-basedness to the outcome for non-academic entrepreneurs, and to detect potential nonlinearities in the impact of research-basedness.

3.3.2.2 Innovation and performance variables

The panel setup is transformed into a cross-section to study innovation. Regarding the innovation indicators, $R\&D$ displays whether the startup had any R&D activities. $Market\ Novelty$ is 1 when a startup introduced any novelty to the market at a regional, national, or worldwide level. On the other hand, $World\ Novelty$ is only 1 when the innovation was novel worldwide. With regards to sales, the panel survey indicates the sales for a specific year in dollars. We transform these into variables of sales for each of the first five years of the firm in the cross-sectional approach. Then we transform these into log sales by taking the log of the sales amount plus one. Concerning the sales analyses, the sales are transformed into a panel setup with the firm's age as the time dimension. Similarly, we construct the variables for accumulated sales. From the log sales, we construct two additional variables: first sales and the amount of sales conditional on having sales. The former is coded as a dummy whether the startup received their first sales that year or if they had received their first sales already in the previous years, as 1, and 0 if they did not. The latter is the amount of sales (in US dollars) conditional on having sales (sales > 0).

3.3.2.3 Control variables

First, we introduce a categorical variable including five industry classes, in line with the classification by Galindo-Rueda and Verger (2016), i.e., high-tech manufacturing, software, knowledge-intensive services, low-tech manufacturing, and others. The dummies of education indicate whether at least one of the founders has obtained higher education in one of the listed fields (*Education Science, Education Engineering, Education Social Sciences, Education Humanities and Arts*, and *Education Other fields*). Germany is divided into three regions due to the significant influences of the past, constituting regional differences between East-, West Germany, and Berlin. The category of West Germany is represented by the reference level, and dummies *Berlin* and *East* represent the other regions. Moreover, the *Team* dummy refers to startups that have more than one founder in the founding team, while *Female* represents founding teams with at least one female founder. *Founder(s) age* is constructed as the average of the ages of the youngest and oldest members of the founding team. Furthermore, *Number of patents* before founding indicates how many patents the founders started their company with. *Opportunity entrepreneurship* illustrates whether the startup was founded due to an opportunity or out of necessity. In addition, *Unemployment before startup* indicates if one of the founders was unemployed right before the founding of the firm.

3.3.3 Empirical strategy

To analyze the innovation outcomes of the different types of academic startups, we use a robust OLS regression model in a cross-sectional setup:

$$\begin{aligned} Y_i = \sum_{j=1}^{4} \beta_j * Research-based\, academic\, startup\, quartile_{ij} \\ +\beta * Controls_i + \epsilon_i \end{aligned} \tag{3.1}$$

With Y_i the innovation outcomes: R&D, market novelty, and world novelty, included as dummies. The independent variable is a categorical variable depicting the four quartiles of research-based academic startups, with the non-academic startups as the base level category. The controls include the earlier outlined startup and team characteristics, and in the case of market and world novelty, also include R&D.

To analyze the new venture's sales, we reconstruct the cross-sectional setup into

a panel setup with the time dimension, the firm's age. This allows a more cohesive assessment of the sales evolution in the first five years of inception. Two main model specifications are included, one without interaction and one with interaction of startup types and firm age. The mathematical equation for the simplistic model without interaction:

$$Logsales_{it} = \sum_{j=1}^{4} \beta_j * Research-based\ academic\ startup\ quartile_{itj} + \sum_{k=1}^{t} \beta_k * Firm\ age_{itk} + \beta * Controls_{it} + \epsilon_{it} \tag{3.2}$$

The outcome variable is the logarithm of sales. The independent variable is the categorical variable with non-academic startup and the four research-based academic startup quartiles, with the time dimension being the firm's age. The specification includes as controls the startup and founding team characteristics, R&D, and calendar year fixed effects. The specification with the interaction effect (not shown here) makes it possible to follow each research-based academic quartile startup's sales evolution for each of their first five years. In an extension, we pull apart the possible mechanisms driving the sales effects and look at outcome variables: first sales (dummy), and the amount of sales conditional on having sales.

Additionally, robustness tests are conducted. For innovation, specifically, these include logit and probit regressions, while for sales, we estimate robustness tests with (log) accumulated sales and fixed effects specifications. For both innovation and sales we conduct the following robustness tests: (i) inclusion of human capital variables (i.e., industry experience and startup experience), (ii) inclusion of private venture capital, (iii) inclusion of inverse probability weights of surviving (depending on probability of not exiting and insolvency), and (iv) an alternative specification of the research question by separating the extensive and intensive margins in two models. This approach would consist of estimating two models: (1) a model specification comparing non-academic startups and all academic startup types grouped (i.e., extensive margin), and (2) a model with a continuous variable for research-basedness to fully capture the academic startup's diversity (i.e., intensive margin), (v) use the underlying research-based variables as individual independent variables (i.e., research abilities, research method, and research results), and (vi) include an interaction with the share of academicness corresponding to the relative academic-

ness of the team in relation to team size.

3.4 RESULTS

3.4.1 Descriptives

Table 3.1 provides an overview of all the main variables of our analyses. The summary statistics are shown for the cross-sectional approach to the Startup panel dataset.

As earlier indicated in section 3.3.2.1, we utilize a factor analysis to examine the dimensionalities of the academic's research-basedness in their applied research-related skills, methods, and results. The analysis returns one factor that correlates positively with abilities, methods, and results, as shown in the Appendix in Table B1. The Kaiser-Meyer-Olkin measure (0.72) and the Cronbach's alpha (0.85) point to the direction that the three variables measure the same construct: to what extent a startup is research-based. As a result, this paper reduces the multidimensional construct of research-basedness to a single dimension.

As academic startups differ from non-academic startups at their base level (e.g., Agarwal and Shah, 2014; Coad et al., 2021; Colombo and Piva, 2008, 2012; Ensley and Hmieleski, 2005; Goel and Grimpe, 2012; Löfsten and Lindelöf, 2005; Mathisen and Rasmussen, 2019; Shane, 2004; Visintin and Pittino, 2014; Wright et al., 2006), we estimate a multinomial logit model in Table B2 in the Appendix to show the divergent probabilities of being a certain type of startup (non-academic, or a specific research-based quartile academic startup) depending on firm and founding team characteristics. In Table B3 in the Appendix, the corresponding marginal effects are shown. As expected, academic startups are more present in the software, knowledge-intensive services, and high-tech manufacturing industries. While the highest quartiles of research-based academics are more likely to be situated in the high-tech manufacturing industry, research-based academics in the middle to high quartiles are more likely to be situated in software and knowledge-intensive services. Academic startups in general often have founders from a science background in their founding team, while higher research-based academic teams are also more dominant in Engineering. Surprisingly, lower research-based academic startups have an older founding team. Higher research-based academic startups obtain more patents before founding, have less prior startup and industry expe-

Table 3.1: Descriptives table

	Count	Mean	Sd	Min	Max
Non-academic startup	5873	0.852	0.355	0	1
Research-based academic startup quartile 1	5873	0.044	0.205	0	1
Research-based academic startup quartile 2	5873	0.035	0.184	0	1
Research-based academic startup quartile 3	5873	0.043	0.203	0	1
Research-based academic startup quartile 4	5873	0.026	0.160	0	1
Academic startup	5873	0.148	0.355	0	1
Research-basedness academic	871	3.556	2.842	0	9
R&D	5873	0.269	0.443	0	1
Market Novelty	5873	0.310	0.462	0	1
World Novelty	5873	0.127	0.333	0	1
Other industries	5873	0.211	0.408	0	1
Software	5873	0.135	0.341	0	1
Knowledge-intensive services	5873	0.412	0.492	0	1
High-tech manufacturing	5873	0.134	0.341	0	1
Low-tech manufacturing	5873	0.108	0.311	0	1
Founding year = 2007	5873	0.029	0.169	0	1
Founding year = 2008	5873	0.033	0.177	0	1
Founding year = 2009	5873	0.038	0.192	0	1
Founding year = 2010	5873	0.053	0.225	0	1
Founding year = 2011	5873	0.074	0.262	0	1
Founding year = 2012	5873	0.093	0.291	0	1
Founding year = 2013	5873	0.148	0.355	0	1
Founding year = 2014	5873	0.162	0.368	0	1
Founding year = 2015	5873	0.160	0.366	0	1
Founding year = 2016	5873	0.132	0.338	0	1
Founding year = 2017	5873	0.077	0.267	0	1
Education Science	5873	0.231	0.422	0	1
Education Engineering	5873	0.401	0.490	0	1
Education Social Sciences	5873	0.443	0.497	0	1
Education Humanities and Arts	5873	0.092	0.288	0	1
Education Other fields	5873	0.014	0.117	0	1
Region = West	5873	0.810	0.392	0	1
Region = Berlin	5873	0.067	0.251	0	1
Region = East	5873	0.122	0.327	0	1
Team	5873	0.452	0.498	0	1
Female	5873	0.201	0.401	0	1
Founder(s) age	5873	42.438	9.748	19	95
Number of patents before founding	5873	0.221	2.210	0	100
Startup Experience	5873	0.521	0.500	0	1
Industry Experience	5873	14.067	10.131	1	60
Opportunity Entrepreneurship	5873	0.879	0.326	0	1
Unemployment before startup	5873	0.075	0.263	0	1
Log sales in first year	5415	8.519	4.772	0	19.114
Log sales in second year	4087	10.934	3.542	0	20.436
Log sales in third year	2981	11.639	3.001	0	18.064
Log sales in fourth year	2011	11.987	2.735	0	18.198
Log sales in fifth year	1402	12.226	2.546	0	17.281
Log accumulated sales in first year	5415	8.519	4.772	0	19.114
Log accumulated sales in second year	3949	11.295	3.478	0	20.436
Log accumulated sales in third year	2559	12.430	2.824	0	18.386
Log accumulated sales in fourth year	1495	13.122	2.457	0	18.989
Log accumulated sales in fifth year	900	13.701	2.016	0	18.133

rience, and start their company with an opportunity motivation. The divergence in the academic startup's characteristics might be attributed to divergent driving characteristics into entrepreneurship. Goel and Grimpe (2012) show that general academic entrepreneurship is not driven by some key drivers of research-based entrepreneurship, such as patent applications, scientific leadership, and engineering

sciences. This is in line with our findings above. Given that the characteristics of the startup types (and founders) and the driving characteristics for academics' selecting into entrepreneurship differ, firm and founding team characteristics will be taken into account in the following analyses as control variables to mitigate selection biases as best as possible.

3.4.2 Innovation

In the innovation context, higher research-based academic startups invest more in R&D compared to non-academic startups and academic startups that do not use or use to a lower extent their research result (Table 3.2, column (1)). Research-based academic startups in the 3rd quartile are 20.8% ($p < 0.01$) more likely to conduct R&D activities compared to non-academic startups, while this is 30.0% ($p < 0.01$) for research-based academics in the 4th quartile. To a considerably smaller extent, research-based academics in the 1st quartile (i.e., non-research-based academics) are 4.8% ($p < 0.1$) more likely than non-academics to invest in R&D. Testing the coefficients of the research-based academic startup quartiles, only the first and second quartiles are statistically insignificant from each other. Thus, research-based academics from the 3rd quartile invest more in R&D than academics in the 1st and 2nd quartile, while academics in the last quartile invest significantly more than all other academic startups. In other words, the more research-based the academic startup, the more likely to invest in R&D.

In terms of market and world novelties, the most research-based academic startups have a higher likelihood of introducing novelties (Table 3.2, columns (2), (3), (4), and (5)). When R&D is not controlled for, all academic startups, irrespective of their research-basedness (quartiles 1 to 4), are more likely to introduce market novelties compared to non-academics (Table 3.2, column (2)). However, column (3) shows that a large amount of the effect could be attributed to more investments in R&D, rendering an insignificant effect for academic startups in quartiles 1 and 3. However, research-based academics in the 4th quartile are still 11.8% ($p < 0.01$, column (3)) more likely than non-academics to introduce market novelties. On the other hand, using limited research-related knowledge, academic startups of the 2nd quartile, are also 6.7% ($p < 0.05$, column (3)) more likely than non-academics to produce market novelties. Testing the coefficients of the quartiles reveals no significant divergence within academic startup categories.

Considering world novelties, the higher research-based academics (3rd and 4th

Table 3.2: Innovation

	R&D	Market Novelty		World Novelty	
	(1)	(2)	(3)	(4)	(5)
Research-based academic quartile 1	0.048*	0.061**	0.047	0.026	0.016
	(0.028)	(0.030)	(0.029)	(0.023)	(0.022)
Research-based academic quartile 2	0.045	0.080**	0.067**	0.033	0.024
	(0.031)	(0.033)	(0.033)	(0.025)	(0.025)
Research-based academic quartile 3	0.208***	0.109***	0.049	0.072***	0.029
	(0.029)	(0.032)	(0.032)	(0.026)	(0.025)
Research-based academic quartile 4	0.300***	0.205***	0.118***	0.181***	0.119***
	(0.039)	(0.041)	(0.040)	(0.038)	(0.038)
Software	0.307***	0.128***	0.038*	0.097***	0.035**
	(0.021)	(0.023)	(0.023)	(0.017)	(0.017)
Knowledge-intensive services	0.090***	-0.033**	-0.059***	0.010	-0.008
	(0.013)	(0.016)	(0.016)	(0.010)	(0.009)
High-tech manufacturing	0.412***	0.179***	0.059**	0.202***	0.117***
	(0.021)	(0.023)	(0.023)	(0.019)	(0.018)
Low-tech manufacturing	0.144***	0.048**	0.005	0.060***	0.031**
	(0.019)	(0.022)	(0.021)	(0.015)	(0.014)
Founding year	0.024***	-0.002	-0.009***	0.001	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Berlin	0.050**	0.036	0.022	0.049**	0.039**
	(0.023)	(0.024)	(0.023)	(0.019)	(0.019)
East	-0.033**	-0.034*	-0.025	-0.039***	-0.032***
	(0.016)	(0.018)	(0.017)	(0.012)	(0.011)
Education Science	0.122***	0.110***	0.074***	0.066***	0.041***
	(0.018)	(0.020)	(0.020)	(0.015)	(0.015)
Education Engineering	0.110***	0.061***	0.029	0.030**	0.007
	(0.017)	(0.019)	(0.019)	(0.014)	(0.014)
Education Social Sciences	0.061***	0.107***	0.089***	0.043***	0.030**
	(0.016)	(0.018)	(0.018)	(0.014)	(0.013)
Education Humanities and Arts	0.086***	0.091***	0.066***	0.038**	0.020
	(0.021)	(0.025)	(0.024)	(0.017)	(0.017)
Education Other fields	0.063	0.032	0.014	0.075*	0.062*
	(0.042)	(0.051)	(0.048)	(0.039)	(0.037)
Team	0.045***	0.028**	0.015	0.012	0.003
	(0.012)	(0.013)	(0.012)	(0.009)	(0.009)
Female	-0.081***	-0.049***	-0.025*	-0.035***	-0.019**
	(0.013)	(0.015)	(0.015)	(0.010)	(0.010)
Founder(s) age	-0.000	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Number of patents before founding	0.007*	0.012***	0.010***	0.009**	0.007*
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Opportunity Entrepreneurship	0.033**	0.064***	0.054***	0.029***	0.023**
	(0.015)	(0.017)	(0.016)	(0.011)	(0.011)
Unemployment before startup	-0.014	-0.020	-0.016	-0.030**	-0.027**
	(0.019)	(0.021)	(0.021)	(0.013)	(0.013)
R&D			0.292***		0.204***
			(0.016)		(0.013)
Research: cat 1 vs cat 2	0.943	0.658	0.638	0.830	0.811
Research: cat 1 vs cat 3	0.000	0.257	0.960	0.169	0.683
Research: cat 1 vs cat 4	0.000	0.003	0.143	0.000	0.017
Research: cat 2 vs cat 3	0.000	0.515	0.685	0.271	0.873
Research: cat 2 vs cat 4	0.000	0.015	0.313	0.001	0.034
Research: cat 3 vs cat 4	0.050	0.056	0.162	0.016	0.045
Observations	5873	5873	5873	5873	5873
R^2	0.184	0.072	0.136	0.082	0.143

Note: Base category: Non-academic startups. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

quartile) are more likely to introduce world novelties (column (4)). However, taking R&D activities into account, only the research-based academics in the 4th quartile are more likely to introduce world novelties, at 11.9% ($p < 0.01$, column (5)), compared to non-academics. They also appear to be more likely to introduce world novelties compared to their academic counterparts (i.e., 1st quartile ($p = 0.017$); 2nd quartile ($p = 0.034$), and 3rd quartile ($p = 0.045$)).

The logit and probit specifications are robust (Table B4). Similarly for the specification including the human capital variables, industry experience and startup experience (Table B5, columns (1), (2), (3)) with the minor exception that the significance is reduced of the research-based academic startups in the 2nd quartile ($p < 0.1$) on market novelty (Table B5, column (2), $p < 0.1$). In relation to VC, we include whether the firm received private VC investments in the first five years of inception (Table B5, columns (4), (5), (6)). Receiving these investments significantly increases the likelihood of producing innovations, but does not alter the previous findings, which thus remain robust. Concerning exit and insolvency (Table B6), low-research-based academic startups in the first quartile are more likely to exit, while those in the second quartile are more likely to exit due to insolvency (columns (1) and (2)). However, the results remain robust with the inclusion of the inverse probability weights of surviving (i.e., no exit or insolvency) to take any potential survival bias into account. When introducing a divergent manner of modeling the research setup into two models, separating extensive and intensive margins (Table B7), the results are in line with our general model's findings. Academic startups, compared to non-academic startups, conduct more R&D, market novelties, and world novelties. The higher the research-basedness of the academic, the more R&D they will conduct (3.3%, $p < 0.01$). In terms of world novelty, the results incline towards a higher research-basedness score, the higher the chance of introducing a world novelty (0.9%, $p < 0.1$). Taking into account that research-basedness is a continuous scale in this model and takes marginal incremental steps in terms of research-basedness, the results appear to be robust compared to the main model in which the fourth research-based quartile introduces significantly more world novelties compared to the other quartiles (Table 3.2, column (3)). Although factor analysis shows the construct validity of research-basedness, we run additional analyses for the individual underlying variables, i.e., research abilities, research methods, and research results (Table B8). The results are in line with our main analyses and do not follow distinct individual patterns. Lastly, we introduce an interaction effect of the *share of academicness* into the analyses (Table B9). The *share of academic-*

ness is constructed by having at least 1 academic founder in the founding team (dummy) divided by team size. The analyses do not appear to bring new insights and are robust, corresponding with the main analyses. Thus, the additional analyses show a high robustness for the higher innovativeness of high research-based academic startups in the 4th quartile.

In summary, especially academic startups scoring high on research-basedness (mostly 4th quartile) are more innovative in terms of R&D, market novelty, and world novelty, compared to non-academics, which confirms hypothesis H1a. Limited research-based academics (2nd quartile) manage to establish more market novelties than non-academics, and thus have an innovative advantage, in line with hypothesis H1c, although to a much smaller extent than high research-based academic startups (confirming hypothesis H1b).

3.4.3 Growth

Regarding sales performance, academic startups with higher research-based scores have lower sales numbers (Table 3.3). In the basic model (column (1)), research-based academics in the 3rd quartile have lower sales at a 10% significance level, while research-based academics in the highest quartile on average have 79% lower sales than non-academics (β=-1.539, $p < 0.01$).[2] For the year dummies, all coefficients are significant and increase over time (captured in the firm age FE). This is to be expected as sales grow over the years, and the average startup in its second year will make fewer sales compared to the average startup in its fifth year. In model (2), industry FE, other startup characteristics, and founding team characteristics are introduced.[3] In addition, model (3) includes calendar year fixed effects. Thus in our main model (column (3)), research-based academic startups in the highest quartile (4th quartile) on average have 65% lower sales compared to non-academic startups (β=-1.056, $p < 0.01$).[4] In models (4), (5), and (6), an interaction effect of the research-based quartiles and the firm age is introduced. For the interaction effects of the research-based variables with the firm's age, only *Research-based Q4 x Firm age = 5* is significant ($p < 0.05$). It shows that the highest research-based academic firms (4th quartile) are only able to catch up their lag in sales in their fifth year of existence, given that the coefficient of the interaction effect (β=1.565) will

[2] calculation:$e^{-1.539} - 1 = -0.7854$

[3] Other startup characteristics: region and founding year fixed effects. Founding team characteristics: Fields of education, team, female, founder(s) age, number of patents, opportunity entrepreneurship, and unemployment before startup.

[4] calculation:$e^{-1.056} - 1 = -0.6522$

Table 3.3: Sales

	Log Sales					
	Without interaction			With interaction		
	(1)	(2)	(3)	(4)	(5)	(6)
Research-based Q1	-0.003	0.108	0.153	0.076	0.153	0.196
	(0.186)	(0.189)	(0.189)	(0.319)	(0.319)	(0.320)
Research-based Q2	-0.120	-0.071	-0.041	0.031	0.048	0.091
	(0.207)	(0.208)	(0.207)	(0.346)	(0.348)	(0.348)
Research-based Q3	-0.391*	-0.009	0.018	-0.581*	-0.260	-0.224
	(0.203)	(0.206)	(0.206)	(0.330)	(0.323)	(0.324)
Research-based Q4	-1.539***	-1.121***	-1.056***	-1.961***	-1.559***	-1.488***
	(0.336)	(0.328)	(0.327)	(0.446)	(0.439)	(0.439)
Research-based Q1 × Firm age=2				-0.149	-0.141	-0.130
				(0.305)	(0.305)	(0.306)
Research-based Q1 × Firm age=3				-0.012	0.013	0.019
				(0.324)	(0.327)	(0.325)
Research-based Q1 × Firm age=4				-0.043	0.043	0.045
				(0.349)	(0.350)	(0.350)
Research-based Q1 × Firm age=5				-0.256	-0.138	-0.166
				(0.368)	(0.372)	(0.373)
Research-based Q2 × Firm age=2				-0.588*	-0.534	-0.544
				(0.335)	(0.335)	(0.336)
Research-based Q2 × Firm age=3				0.001	0.006	-0.020
				(0.342)	(0.341)	(0.343)
Research-based Q2 × Firm age=4				-0.051	0.020	-0.006
				(0.379)	(0.381)	(0.382)
Research-based Q2 × Firm age=5				0.034	0.095	0.086
				(0.423)	(0.434)	(0.437)
Research-based Q3 × Firm age=2				0.082	0.067	0.062
				(0.331)	(0.330)	(0.330)
Research-based Q3 × Firm age=3				0.170	0.249	0.240
				(0.340)	(0.339)	(0.341)
Research-based Q3 × Firm age=4				0.499	0.629*	0.614*
				(0.362)	(0.363)	(0.364)
Research-based Q3 × Firm age=5				0.472	0.685*	0.649
				(0.403)	(0.410)	(0.411)
Research-based Q4 × Firm age=2				0.179	0.177	0.202
				(0.423)	(0.420)	(0.420)
Research-based Q4 × Firm age=3				0.610	0.653	0.674
				(0.493)	(0.487)	(0.486)
Research-based Q4 × Firm age=4				0.400	0.421	0.393
				(0.528)	(0.520)	(0.525)
Research-based Q4 × Firm age=5				1.601***	1.658***	1.565***
				(0.543)	(0.534)	(0.537)
R&D		-0.548***	-0.555***		-0.551***	-0.558***
		(0.123)	(0.123)		(0.123)	(0.123)
Research: cat 1 vs cat 2	0.664	0.508	0.470	0.922	0.820	0.819
Research: cat 1 vs cat 3	0.147	0.661	0.610	0.142	0.347	0.339
Research: cat 1 vs cat 4	0.000	0.001	0.001	0.000	0.001	0.002
Research: cat 2 vs cat 3	0.337	0.825	0.834	0.190	0.504	0.495
Research: cat 2 vs cat 4	0.000	0.006	0.007	0.000	0.003	0.004
Research: cat 3 vs cat 4	0.003	0.003	0.004	0.012	0.014	0.017
Firm age FE	YES	YES	YES	YES	YES	YES
Industry FE	NO	YES	YES	NO	YES	YES
Calendar time FE	NO	NO	YES	NO	NO	YES
Other startup characteristics	NO	YES	YES	NO	YES	YES
Founding team characteristics	NO	YES	YES	NO	YES	YES
Observations	15896	15896	15896	15896	15896	15896
Groups (Firms)	5660	5660	5660	5660	5660	5660
R^2	0.138	0.170	0.172	0.138	0.170	0.173

Note: Base category: Non-academic startup. "Research-based Q1" refers to "Research-based academic quartile 1". Standard errors in parentheses. Standard errors clustered by firm. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

balance out the general negative effect for being a high research-based academic firm (β=-1.488) (column (6)).

Concerning the robustness tests, the results are robust when using accumulated sales (Table B10, columns (3), (4), (5), and (6)), with the inclusion of human capital variables (Table B11, columns (1)-(4)), with the inclusion of Private VC as control (Table B11, columns (5)-(6)), and inverse probability weights to correct for survival bias (Table B12). The two models approach shows that academic startups in general are not significantly different in sales compared to non-academic startups (Table B13, columns (1) and (2)). However, the more research-based the academic startup, the lower the startup's sales numbers (β=-0.166, column (2) and (4), $p < 0.01$). The fixed effects specification (Table B10, columns (1) and (2)) appears to be too stringent for a significant interaction effect of the 4th quartile research-based academics in their fifth year. The robustness tests regarding the individual variables of the research-basedness construct (i.e., research abilities, methods, and results) (Table B14) and the inclusion of an interaction term for the share of academicness (Table B15) are overall robust.

As a result, the general effect that high-research-based academic start-ups in the 4th quartile lag in sales is robust, thus confirming hypotheses H2a and H2b. Moreover, robust in all POLS specifications, these highly research-based academic startups appear to catch up in their fifth year.

3.4.3.1 Extension: First sales and conditional sales amount

In the following extension (Table 3.4), the effect of sales performance is examined in deeper detail and pulled apart into two elements: (1) the time to first sales, and (2) the amount of sales conditional on having sales. Column (1) shows that highly-research-based academic startups (4th quartile) are 5% less likely to achieve a first sales in the five-year time frame compared to non-academics (β=-0.048, $p < 0.05$).[5] They are also significantly less likely to achieve first sales compared to the other academic startup quartiles in these early years (i.e., column (1), 1st quartile ($p = 0.003$); 2nd quartile ($p = 0.014$), and 3rd quartile ($p = 0.022$)). When taking the timing interaction effect into account (column 2), the overall effect for *Research-based academic quartile 4* is negative (β=-0.127, $p < 0.01$). However, the coefficients of the interaction terms *Research-based academic quartile 4 x Firm age = 3*, *Research-based academic quartile 4 x Firm age = 4*, *Research-based academic*

[5] calculation: $e^{-0.048} - 1 = -0.0468$

quartile 4 x Firm age = 5 are statistically significant positive (respectively, 0.100, $p < 0.01$; 0.102, $p < 0.01$; 0.147, $p < 0.01$), counterbalancing the overall negative effect. Thus, high-research-based academic startups in the 4th quartile generally take longer to achieve their first sales, and only manage to catch up in their third year after founding.

Concerning the amount of sales, in the basic model (column (3)), research-based academics in the 3rd quartile have 15% lower sales at a 10% significance level (β=-0.157), while research-based academics in the highest quartile on average have 32% lower sales than non-academics conditional on having sales (β=-0.383, $p < 0.01$).[6] Column (4) shows that the overall negative effect for research-based academics in the 4th quartile persists (β=-0.415) with no evidence of improvement in the first five years, as no interaction term of the 4th academic quartile with the firm's age is significant. Thus, highly research-based (4th quartile) academic startups have significantly lower sales levels in their early years of conception (given that they have sales) with no indication of reducing that gap in the first five years.

[6] calculation: $e^{-0.383} - 1 = -0.3182$

Table 3.4: First sales and amount of sales conditional on sales

	First Sales		Sales if sales > 0	
	(1) without	(2) with	(3) without	(4) with
Research-based academic quartile 1	0.016*	0.016	-0.131	-0.015
	(0.008)	(0.027)	(0.102)	(0.126)
Research-based academic quartile 2	0.006	0.015	-0.128	-0.088
	(0.010)	(0.030)	(0.104)	(0.131)
Research-based academic quartile 3	0.004	-0.018	-0.157*	-0.225*
	(0.011)	(0.029)	(0.084)	(0.117)
Research-based academic quartile 4	-0.048**	-0.127***	-0.383***	-0.415***
	(0.020)	(0.040)	(0.120)	(0.155)
Research-based academic quartile 1 × Firm age=2		0.008		-0.215*
		(0.026)		(0.121)
Research-based academic quartile 1 × Firm age=3		-0.002		-0.081
		(0.027)		(0.155)
Research-based academic quartile 1 × Firm age=4		-0.004		-0.075
		(0.028)		(0.162)
Research-based academic quartile 1 × Firm age=5		-0.003		-0.271
		(0.028)		(0.181)
Research-based academic quartile 2 × Firm age=2		-0.025		-0.011
		(0.026)		(0.136)
Research-based academic quartile 2 × Firm age=3		-0.005		-0.031
		(0.030)		(0.132)
Research-based academic quartile 2 × Firm age=4		-0.009		-0.116
		(0.031)		(0.182)
Research-based academic quartile 2 × Firm age=5		-0.005		-0.096
		(0.030)		(0.247)
Research-based academic quartile 3 × Firm age=2		0.017		0.040
		(0.026)		(0.113)
Research-based academic quartile 3 × Firm age=3		0.015		0.095
		(0.027)		(0.138)
Research-based academic quartile 3 × Firm age=4		0.038		0.140
		(0.029)		(0.133)
Research-based academic quartile 3 × Firm age=5		0.040		0.086
		(0.029)		(0.170)
Research-based academic quartile 4 × Firm age=2		0.054		-0.063
		(0.034)		(0.169)
Research-based academic quartile 4 × Firm age=3		0.100***		0.103
		(0.038)		(0.149)
Research-based academic quartile 4 × Firm age=4		0.102***		0.076
		(0.039)		(0.172)
Research-based academic quartile 4 × Firm age=5		0.147***		0.073
		(0.040)		(0.207)
R&D	-0.032***	-0.032***	0.081	0.081
	(0.005)	(0.005)	(0.053)	(0.053)
Research: cat 1 vs cat 2	0.409	0.970	0.982	0.681
Research: cat 1 vs cat 3	0.367	0.379	0.835	0.204
Research: cat 1 vs cat 4	0.003	0.003	0.100	0.040
Research: cat 2 vs cat 3	0.896	0.423	0.819	0.418
Research: cat 2 vs cat 4	0.014	0.004	0.099	0.098
Research: cat 3 vs cat 4	0.022	0.025	0.103	0.310
Firm age FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Calendar time FE	YES	YES	YES	YES
Other startup characteristics	YES	YES	YES	YES
Founding team characteristics	YES	YES	YES	YES
Observations	26411	26411	14113	14113
Groups (Firms)	5660	5660	5236	5236
R^2	0.144	0.145	0.198	0.198

Note: Base category: Non-academic startup. Standard errors in parentheses. Standard errors clustered by firm. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

3.5 DISCUSSION AND CONCLUSION

3.5.1 Discussion

This study provides new insights into the heterogeneity within academic entrepreneurship by moving beyond the traditional divide between general academic startups and research spin-offs. Instead, we introduce a more nuanced categorization that captures varying degrees of research-basedness, ranging from startups that do not utilize research-related knowledge to those where research is a fundamental component of venture creation. Our findings emphasize the pivotal role of research-basedness in shaping innovation and performance outcomes. Research-based academic startups, particularly those in the highest quartile of research intensity, exhibit superior R&D investments, market novelty, and world novelty compared to both non-academic and less research-intensive academic startups. However, they experience a significant lag in sales performance, only catching up after five years. They are less likely to have achieved their first sales in the first three years of inception and lag behind in sales numbers (conditional on having sales) for at least the first five years. These results align with prior literature suggesting that research-based startups benefit from strong technological competencies but face commercialization challenges (Löfsten and Lindelöf, 2005; Mathisen and Rasmussen, 2019; Shane, 2004; Tartari and Stern, 2021).

Our findings suggest that academic entrepreneurship should not be treated as a monolithic category. While highly research-based academic startups closely resemble traditional academic spin-offs in their innovation advantages (Colombo and Piva, 2008), lower research-based academic startups demonstrate a distinct profile. Despite leveraging their specific research methods, abilities, or results to a limited extent, they still achieve higher market novelty than non-academic startups. This aligns with the argument that academic environments enhance individuals' opportunity recognition skills, even when their ventures do not directly utilize research outputs (Criaco et al., 2014; Nagle and Teodoridis, 2020; Ronstadt, 1988). Additionally, our results reveal an important nonlinearity: research-based academic startups that fall in the third quartile, those that are research-focused but do not fully commit to leveraging their research-related knowledge, appear to be less effective at converting their human capital advantage into innovation outcomes. While they invest significantly in R&D, their innovation performance does not match this input when controlling for R&D intensity. This suggests a limitation in how they

leverage their human capital. Given that lower research-based academic startups (second quartile) are more likely to introduce market novelties, our results indicate that academic entrepreneurs may benefit from aligning their strategy, either fully embracing a research-based approach or limiting their research-related acquired capabilities, rather than remaining in an ambiguous middle ground.

From a human capital perspective, our findings reinforce the idea that general and specific human capital influence innovation and performance differently. Research-intensive academic entrepreneurs possess high levels of specific human capital in the form of technological expertise, which facilitates radical innovation (Colombo and Piva, 2012; Marvel and Lumpkin, 2007). However, their limited market knowledge may hinder their commercialization efforts, explaining their initial sales disadvantage (Mathisen and Rasmussen, 2019; Wright et al., 2006). Conversely, academic entrepreneurs with lower research-basedness leverage their education and research experience as general human capital, contributing to their ability to introduce novel products despite lacking the technological edge of research-intensive startups (Ganotakis, 2012; Rauch and Rijsdijk, 2013). The inefficiency observed in high-mid-tier research-based startups further suggests that partial application of research expertise may not be sufficient to yield competitive advantages.

3.5.2 Implications

The findings of this study carry significant implications for both academic entrepreneurship research and policy design. First, they contribute to the literature by providing a more granular understanding of how varying levels of research-basedness influence innovation and growth. This distinction helps explain inconsistencies in prior research regarding the performance outcomes of academic startups (Czarnitzki et al., 2014; Wennberg et al., 2011). Our results suggest that research-intensive academic startups drive technological advancements, whereas those with lower research-basedness still, to a smaller extent, contribute to market novelty, highlighting complementary roles in the entrepreneurial ecosystem.

Second, policymakers aiming to foster academic entrepreneurship should consider these distinctions. Policies promoting university-industry knowledge spillovers should prioritize mechanisms that support research-intensive startups' commercialization efforts, such as mentorship programs, R&D tax credits, marketing & general management skills classes, commercialization coaching, and market access initiatives (Colombo and Piva, 2012). Especially, academic entrepreneurship education

and training have been found to be effective in improving entrepreneurial outcomes, such as early growth (Davidsson and Honig, 2003; Martin et al., 2013). Thus, in an effort to reduce the high research-based academic startup's early-stage growth gap, universities can offer entrepreneurship and (entrepreneurial) management courses to these research-based academic founders. Simultaneously, academic startups with lower research-basedness, which exhibit a balance between novelty and growth, may benefit from policies that enhance the wider applicability of scientific thinking in encouraging opportunity recognition and exploitation through designing opportunity recognition and business model workshops, and cross-disciplinary networking events with academics and industry mentors in interdisciplinary fields (Ganotakis, 2012; Marvel et al., 2020; Mosey and Wright, 2007; Nagle and Teodoridis, 2020; Visintin and Pittino, 2014; Wright et al., 2006). Furthermore, the inefficiency observed in high-mid-tier research-based startups (in the third quartile) suggests the need for targeted interventions to ensure that firms investing in R&D can translate those investments into tangible innovation outcomes. Policymakers could encourage clearer strategic positioning by designing programs (e.g., strategic positioning clinics with expert-led workshops that guide teams, customized resource allocation advice) that help startups either fully integrate research-based competencies or focus on alternative sources of innovation.

Finally, the trade-off between innovation and growth observed in research-intensive academic startups underscores the need for targeted support structures. While these startups excel in technological breakthroughs, their delayed sales performance suggests challenges in transitioning from research to market application. This reinforces the necessity for incubation programs that bridge the gap between research excellence and commercial viability (Agarwal and Shah, 2014; Goel and Grimpe, 2012).

3.5.3 Limitations

We recognize that our study cannot make any causal claims but is rather observational and descriptive in nature. However, we do try to control for the extent possible for selection and omitted variable bias by including control variables and addressing selection bias due to exit.

We recognize that selection bias might arise due to divergent characteristics driving academics' selection into entrepreneurship (Goel and Grimpe, 2012). We show in the descriptives with a multinomial logit specification that academic startups' characteristics are divergent across the different types of startups, and thus take

into account firm and founder characteristics as controls in our empirical analyses to account for this bias to the best of our abilities.

Further investigation into the specific contributions of academic founders within founding teams could uncover additional mechanisms through which these individuals shape their startups. In this study, we account for team dynamics as best as possible by controlling for key founding team characteristics (e.g., whether at least one founder has an engineering background, the highest level of industry experience among founders, and the presence of prior entrepreneurial experience). However, as our data is limited to the team level rather than the individual founder level, we cannot disentangle the distinct contributions or relational dynamics of specific founders. Moreover, our exploratory interaction analyses between founding team characteristics and the degree of research-basedness yielded no significant results, likely due to sample size constraints. Therefore, we encourage future research to delve deeper into the interplay between founder-level attributes, particularly how academic founders of varying research intensity engage with their co-founders. Such inquiry could build on the findings of Hsu (2022), who shows that the characteristics of academic founders, especially their research orientation (operationalized as published in the peer-reviewed scientific literature), can decisively shape co-founders' influence on venture outcomes, depending on the fit of the academic founder's domain of expertise and the ventures core business. Bringing these co-founder relations into the context of the research-basedness spectrum of academic startups could lead to interesting new research avenues. Another possible future avenue would be to add the academic founder's founding process into the conversation, in particular, the academic founder's decision-making process in assembling the entrepreneurial team composition. Depending on the academic founder's intentions, they might purposely choose to focus on a homogeneous technological team or diversify their team with commercially experienced founders (Zellmer-Bruhn et al., 2021), which could influence post-foundation startup performance.

Future research could further explore how industry-specific dynamics influence these relationships, providing deeper insights into the optimal support mechanisms for academic entrepreneurs. Moreover, longitudinal studies examining the evolution of academic startups beyond the five-year horizon could shed light on their long-term sustainability and impact within the broader entrepreneurial ecosystem.

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Chapter 4

ACCELERATORS IN FOCUS: What Are Necessary Accelerator Design Features To Enable Early-Stage Financing, Post Acceleration?[1]

This study investigates the critical role of accelerator design in enhancing early-stage ventures' access to external equity funding. Drawing on necessity logic, we explore the key necessary conditions in accelerator program design that influence post-acceleration equity investment outcomes. Using necessary condition analysis (NCA) and qualitative comparative analysis (QCA) to examine necessity, we analyze the open-source data from Entrepreneurship Database Program (GALI Initiative) across North America, Latin America, and South Asia. Our results suggest that offering accelerator grants is a necessary condition for securing high post-acceleration equity investments. A structured curriculum emerges as a secondary bottleneck. Region-specific factors, such as demo days in North America and an impact focus in South Asia, are necessary to attract any equity investments.

By shedding light on necessity "in degree" and "in kind", this study contributes to our understanding of accelerator's role in obtaining early-stage financing, post-acceleration.

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4.1 INTRODUCTION

Accelerators are widely recognized as a crucial element of any entrepreneurial ecosystem (Assenova and Amit, 2024; Bańka et al., 2023; Bergman and McMullen, 2022; Cohen et al., 2019b; Qin et al., 2019; Sohail et al., 2023; Torres and Godinho, 2022), drawing significant scholarly, practitioners', and entrepreneurs' attention (Moritz et al., 2022). This growing interest stems from accelerators' potential impact on new ventures.[2] While anecdotal evidence suggests that only a minority of new ventures achieve unicorn status[3] (Kotha et al., 2022), Y Combinator, one of the first accelerators, consistently maintains a strong record of creating unicorn ventures (Bradbury, 2023), and was widely regarded as inspiration when creating other accelerators (Hallen et al., 2020). Globally, there are a few thousand accelerators (Aljalahma and Slof, 2022), with this number rapidly increasing over the past decade (Drori and Wright, 2018). Despite this, the impact of accelerators remains relatively inadequately understood (Bergman and McMullen, 2022), with prior literature indicating that differences among accelerators may considerably account for differences in new ventures' performance (Chan et al., 2020). This raises the question: What necessary conditions within accelerator programs are crucial for fostering high-growth ventures and securing substantial early-stage funding?

Entrepreneurs, especially in the early-stages of their ventures, face significant challenges: high liability of newness (Bruderl and Schussler, 1990; Stinchcombe, 1965), uncertainty (McKelvie et al., 2011; Mousavi and Gigerenzer, 2014), and resource scarcity (Gupta et al., 2006; Lee and Lévesque, 2023). Accelerators are designed to help entrepreneurs address these challenges by offering a range of crucial resources that support both founders and their ventures (Cohen, 2013; Del Sarto et al., 2020). According to intermediation theory (e.g., Clayton et al., 2018; Ewens et al., 2018; Goswami et al., 2018), accelerators play a central role in bridging the gap between new ventures and key ecosystem agents, such as early-stage investors (Vandeweghe et al., 2019). Empirical research largely supports the notion that accelerators successfully fulfill this intermediary function (e.g., Dalle et al., 2023;

[2] as also reflected in articles such as "Catalyst of Startup Success: How Accelerators Drive Entrepreneurial Finance" (Sable, 2024),"Startup Accelerators Have Become More Popular in Emerging Markets — and They're Working" (Roberts and Kempner, 2017), "Predicting AI's Future from Y Combinator's New Cohort" (Ulan, 2024).

[3] Based on the definition from financial literature, unicorn ventures are: "... private ventures, valued at/over $1 billion and possessing a high, game-changing potential." (Cristofaro et al., 2023, p.457). Also see Kuckertz et al. (2023); Mollick (2020). These ventures are rare, with recent empirical data from Dealroom.com indicating that, globally, only around 150 ventures achieved unicorn status in 2024.

González-Uribe and Reyes, 2021; Venâncio and Jorge, 2022). By selecting high-potential ventures and enhancing their capabilities, accelerators can act as identifiers and developers of high-growth startups, often referred to as gazelles (Beyhan and Fındık, 2022; González-Uribe and Reyes, 2021; Venâncio and Jorge, 2022). Participation in accelerator programs is generally associated with improved access to early-stage financing, primarily by reducing information asymmetries through the signaling of startup quality (Assenova and Amit, 2024; Kotha et al., 2022; Venâncio and Jorge, 2022; Yu, 2020). Nonetheless, some studies caution that accelerator participation may also lead to negative outcomes under certain conditions (Browne et al., 2024). While accelerators generally increase startup performance, their effectiveness varies, and our understanding of why some accelerators foster high-growth startups while others do not remains fragmented (Moroz et al., 2024). This variation is likely tied to the considerable heterogeneity in accelerator design and structure (Bergman and McMullen, 2022; Crișan et al., 2021; Hallen et al., 2020; Phan et al., 2016), which includes differences in learning mechanisms, knowledge spillovers, financial support, and organizational configurations (Cohen et al., 2019b; Piezunka et al., 2022; Posen and Chen, 2013; Winston Smith et al., 2015).

Recent literature has started to determine the accelerator's design features and find an overall beneficial influence of the presence of the design features on the post-acceleration performance of the startup (Assenova and Amit, 2024; Cohen et al., 2019b; González-Uribe and Reyes, 2021; Uhm et al., 2018). Although the positive impact of design features such as a structured curriculum, accelerator grants, and demo days is widely acknowledged (Assenova and Amit, 2024; Cohen et al., 2019b; González-Uribe and Reyes, 2021; Uhm et al., 2018), their relative importance remains debated. González-Uribe and Reyes (2021) argue that the potential to become a high-growth "gazelle" stems from accelerators providing learning, mentorship, and visibility rather than financial support. In contrast, Assenova and Amit (2024) find that accelerator seed funding is almost universally associated with greater startup growth and scaling. Adding another layer of complexity, the importance of design features appears to be highly region-specific, reflecting the varying resources available to accelerators across different regions (Uhm et al., 2018). Thus, there is no overarching consensus regarding which specific accelerator design features are critical to the performance of early-stage ventures.

To address this gap, this study utilizes necessity-based logic through the emerging Necessary Condition Analysis approach (NCA) (Dul, 2016b, 2020; Dul et al., 2023), and is complemented with the fuzzy-set Qualitative Comparative Analysis

approach (fsQCA) (Ragin, 1987, 2008; Rihoux and Ragin, 2009; Vis and Dul, 2018). These approaches may provide novel and informative insights, potentially resolving some of the divergent findings in the literature by identifying whether there are necessary elements or conditions on the accelerators' side and contribute to the understanding of post-acceleration performance variance, utilizing necessity-based logic. This logic suggests that without the identified necessary condition(s), the outcome would not occur (Dul, 2020, 2021). While prior studies are based on sufficiency thinking and use additive logic (e.g., Assenova and Amit, 2024; Posen and Chen, 2013), where variables can compensate for one another to achieve an outcome, necessity logic implies that lack of necessary conditions cannot be offset by higher values in other variable (Dul, 2016b, 2020, 2021). In other words, the necessity logic implies that the absence of X leads to the absence of Y. However, it does not automatically imply that the presence of X (on average) leads to the presence of Y, which is the case for common regression analysis (Dul, 2016b, 2020, 2021). Thus, by utilizing necessity-based logic, this study refrains from evaluating accelerator program design features that lead to higher equity investments, but solely focuses on necessity, that is, identifying key aspects of accelerators without which new ventures would, typically, not be able to secure, post-acceleration, high levels of early-stage financing. Identifying conditions that enable specific outcomes, which are essential for their occurrence, is equally important as examining the factors that drive these outcomes (i.e., sufficiency). This alternative approach can yield valuable new insights for organizational decision-makers (Van Der Valk et al., 2016).

The paper's focus on new ventures securing high early-stage financing is twofold. First, the emphasis on the secured maximum amounts of early-stage financing, post-acceleration, is inspired by insights from the literature (for instance, Freedman, 2008; Ruef and Birkhead, 2024), to learn from unusual data points or patterns. Differently from prior studies on unicorns (e.g., Kotha et al., 2022), we do not give sole attention to extreme outliers defined by a single criterion. Instead, we examine deviations -unusual, higher amounts secured- within the context of the environments in which accelerators operate (with the underlying assumption that these ventures hold potential to, over time, significantly influence their environments and markets). Second, many analytical techniques and empirical strategies recommend treating unusual/extreme points as deviations, often recommending their omission or statistical adjustment (e.g., winsorization, and other approaches) (Aguinis et al., 2013). In light of this, and in line with Gibbert et al. (2021), we argue that unusual cases can provide valuable insights, with an appropriate approach. In our study, we

primarily employed the NCA method, complemented by an analysis using fsQCA. NCA allows for the distinction of necessity at varying levels of the outcome variable Y (i.e., necessity in degree), providing a more granular understanding of necessary conditions that apply only to a specific subset of the sample (Dul, 2016b, 2020). These conditions would neither be sufficient in conventional regression analyses nor necessarily identified in fsQCA, as both approaches rely on the average effect across the full sample. Therefore, utilizing NCA and necessity logic is essential for identifying necessary conditions specific to high-equity post-acceleration investments. VCs balance the costs and benefits of due diligence, conducting less scrutiny for smaller, lower-risk investments and more for larger deals (e.g., Fu and Taylor, 2025; Gompers et al., 2020). In this context, accelerator participation and specific program design features can reduce information asymmetries through credible signals and intermediation (e.g., Hallen et al., 2020; Mayya and Huang, 2025; Vandeweghe et al., 2019; Venâncio and Jorge, 2022), and serve as necessary conditions for securing high levels of VC equity investment.

We utilize the open-source data from the Entrepreneurship Database Program at Emory University, supported by the Global Accelerator Learning Initiative (GALI). The dataset includes information on 408 accelerators with 23,364 applying early-stage ventures, collected between 2013 to 2019, across various industries and regions. Our final sample consists of 171 accelerators and 632 for-profit, first-time accelerator-participating early-stage ventures, from three regions: North America, Latin America, and South Asia. Our results indicate that offering accelerator grants is a necessary condition for securing high post-accelerated equity investments in multiple regions, particularly important for the top 15 percent accelerators in the North American sample. Although playing a less significant role, a structured curriculum becomes a second bottleneck, possibly preventing early-stage accelerated ventures from securing top equity investments. Additionally, region-specific factors, such as demo days in North America and an impact focus in South Asia, are necessary conditions to obtain any amount of equity investments by business angels or venture capital, influencing accelerator effectiveness, emphasizing the need for tailored, context-specific program designs.

By focusing on necessity through the lenses of NCA and QCA methods, our study responds to recent calls in entrepreneurship, management, and strategy literature, extending prior insights with novel perspectives from emerging methodologies (Assenova and Amit, 2024; Del Sarto et al., 2020). By doing so, we contribute to the literature by offering new insights into accelerators' impact on new venture perfor-

mance using necessity logic, rather than utilizing the commonly adopted sufficiency logic in prior studies. Additionally, it offers methodological discussion concerning necessity, integrating two complementary approaches, thereby adding to the literature and prior studies suggesting this as a potential application approach (Torres and Godinho, 2022; Vis and Dul, 2018) in future research. Through NCA and QCA, this study seeks to enrich the entrepreneurship, strategy, and management literature by identifying key necessary conditions for accelerators across different cultural contexts. Given the substantial interest in this topic also from practitioners, policy-makers, and entrepreneurs (Moritz et al., 2022), our findings also hold practical value for these stakeholders, by identifying evidence of key elements that enable new ventures to, first, successfully secure early-stage financing, and second, secure high levels of early-stage financing, post-acceleration. Future research may extend these findings by further exploring whether, and how, these necessary conditions interact with other factors, evolve over time, and their interplay with other elements in the entrepreneurial ecosystem, shaping new venture performance.

4.2 THEORY DEVELOPMENT

4.2.1 Early-stage financing and role of accelerators

Early-stage ventures operate under a high resource scarcity (Gupta et al., 2006; Lee and Lévesque, 2023), with a widely recognized important role of securing initial financial resources (Venâncio and Jorge, 2022) impacting future performance (Åstebro and Bernhardt, 2003; Browne et al., 2024; Colombo and Grilli, 2005). Intermediation theory, as established in the entrepreneurial ecosystem (e.g., Clayton et al., 2018; Goswami et al., 2018) and entrepreneurial finance literature (e.g., Ewens et al., 2018), suggests that accelerators play a crucial role as intermediaries in the co-occurring open-system (i.e., broad, market-facing connections to the wider ecosystem) and closed-system (i.e., controlled, selective engagement with curated stakeholders) intermediation between agents in the ecosystem and new ventures (Vandeweghe et al., 2019). In particular, and in accordance with anecdotal evidence, accelerators can be intermediaries concerning financial resources, and foster connections between new ventures and potential (early-stage) investors (Hoffman and Radojevich-Kelley, 2012). Indeed, prior studies indicate a successful intermediary role, with evidence suggesting that accelerated early-stage ventures are more likely to have higher levels of external equity investments (Browne et al., 2024; Drover

et al., 2017; Hallen et al., 2020; Venâncio and Jorge, 2022; Yu, 2020). Given that early-stage equity investors (e.g., venture capital and business angels) are faced with high information asymmetry (Gompers and Lerner, 2001) when deciding whether to invest in a certain venture, many argue that accelerator participation may serve as a credible signal to the potential investors concerning the quality of early-stage ventures (Kim and Wagman, 2014; Mayya and Huang, 2025; Vandeweghe et al., 2019; Venâncio and Jorge, 2022). Although some recent studies challenge this view (Browne et al., 2024), the majority of prior studies converge on a common insight that accelerators influence the likelihood of securing early-stage equity investment (Assenova and Amit, 2024; Cohen et al., 2019b; Crișan et al., 2021; Jones and Schou, 2023).

While the majority of these studies focus on the comparison between accelerated and non-accelerated ventures, there is relatively limited understanding of the factors contributing to variance in post-acceleration performance, i.e., likelihood of successfully securing early-stage equity investment (Chowdhury and Audretsch, 2024). More specifically, if accelerator participation indeed serves as a credible signal to early-stage equity investors, we are interested in whether there is one specific aspect of accelerators impacting the credibility of this signal, and is a necessary condition to receive high-level early-stage equity investment from venture capital or business angels. Our main focus on investments from venture capital and business angels sources is driven by prior literature indicating that these two financing sources are distinct from other sources (Hellmann et al., 2021) and that receiving investment from these sources may serve as an indication of early-stage venture's high, quality and future potential (Cohen and Wirtz, 2021; Colombo et al., 2010; Hsu, 2004; Lerner and Nanda, 2020; Svetek, 2022). By identifying necessary conditions from the accelerators' side, we posit that our study provides interesting insights into the underlying mechanisms of why accelerator participation can be seen as a good signal of quality. For example, if this signal is always based on whether accelerators are offering initial grants to their participants, we would expect that grant availability is a necessary condition for securing high levels of early-stage investments, across different contexts.

4.2.2 Structure of accelerators

While accelerators are recognized as a unique organizational form (Browne et al., 2024), currently, there is no fixed, universal definition of accelerator (Assenova and

Amit, 2024; Drori and Wright, 2018). However, they are commonly understood as: "learning-oriented, fixed-length programs that provide cohorts of ventures with mentoring and education" (Hallen et al., 2020, p.380), and as cohort-based, limited-in-time programs that "often culminate in a demo day, where startups pitch their progress to a group of investors." (Hochberg and Fehder, 2015, p.1202). In line with Cohen et al. (2019b), defining an accelerator as "a fixed-term, cohort-based program for startups, including mentorship and/or educational components, that culminates in a graduation event." (p.1782). Although the structural diversity of accelerators is well documented (Bergman and McMullen, 2022; Crișan et al., 2021; Hallen et al., 2020), there remains limited consensus on which design features most critically impact startup success, particularly in securing early-stage equity investment. Research shows established accelerators commonly bundle a broad set of features (seed funding, structured curricula, mentorship, demo days, sectoral tracks), consistent with empirical and theoretical accounts of richer program offerings among experienced providers (Assenova and Amit, 2024; Cohen et al., 2019b; Fehder, 2024; Roberts and Lall, 2019). However, program design is strategic and mission-driven rather than size-determined: accelerators intentionally tailor features to sectoral, cohort, and mission priorities, producing purposeful heterogeneity even among experienced accelerators (Assenova and Amit, 2024; Bergman and McMullen, 2022; Chowdhury and Audretsch, 2024; Cohen et al., 2019a,b; Kramer et al., 2023). Existing literature demonstrates that accelerator participation overall is beneficial for startups (e.g., Assenova and Amit, 2024; Cohen et al., 2019b), yet it does not sufficiently differentiate between features that are merely beneficial and those that are indispensable for achieving high levels of equity investment.

To clarify this distinction, we draw on necessity logic, which posits that certain conditions must be present for an outcome to occur, and their absence cannot be compensated for by other factors (Dul, 2020, 2021). Unlike traditional sufficiency-based thinking, necessity logic identifies which features are absolute preconditions for success, particularly in high-stakes environments. This approach is well-suited for studying equity investments, where venture capitalists (VCs) and business angels (BAs) face increasing risk exposure as investment size grows (Ansar et al., 2017). Since VCs conduct less due diligence when it becomes more costly, they balance the costs and benefits of due diligence to find the correct level of scrutiny for each deal (e.g., Fu and Taylor, 2025; Gompers et al., 2020). Given that smaller investment volumes involve lower risk, the relative cost of conducting more thorough due diligence increases, whereas larger deal volumes typically justify more rigorous

processes. In this context, accelerator program participation, and particularly specific program design features, can play a role in reducing information asymmetries through credible signals and intermediation (e.g., Hallen et al., 2020; Mayya and Huang, 2025; Vandeweghe et al., 2019; Venâncio and Jorge, 2022). This implies that certain accelerator design features might become necessary conditions for achieving high levels of VC equity investment.

4.2.3 Regional differences

Y Combinator is widely recognized as a model for accelerator programs worldwide (Hallen et al., 2020), inspiring the widespread adoption of structured startup support globally. Nevertheless, despite this mimicking phenomenon, the regional context remains a crucial determinant of accelerator effectiveness. Accelerators do not operate in a vacuum; they are embedded in and shaped by their entrepreneurial ecosystems, which vary widely in terms of economic landscape, political and legal institutions, culture, investor activity, and equity market maturity (Bliemel et al., 2019; Chowdhury and Audretsch, 2024; Hellmann et al., 2021; Venâncio and Chowdhury, 2022). These contextual conditions influence not only startup financing outcomes but also the design and function of accelerator programs (Fehder and Hochberg, 2014; Goswami et al., 2018). For instance, accelerators in well-developed ecosystems such as Silicon Valley or London benefit from financial infrastructure, dense investor networks, and high levels of financial development (Beck and Demirguc-Kunt, 2006; Caccamo and Beckman, 2022; Florida and Kenney, 1988), whereas those in less developed markets may struggle to access these same resources (Fischer et al., 2022).

North America's accelerator ecosystem is considered mature and competitive (Shetty et al., 2020), with programs like Y Combinator and Techstars setting the global standard (Hochberg, 2016). These accelerators have catalyzed a robust startup environment, where competition among accelerators has led to refined and competitive program structures. Besides a competitive and mature accelerator ecosystem, North America is marked by a mature, high capital availability, and competitive investor environment (Lerner and Nanda, 2020). The U.S. seed-stage venture capital market alone is projected to reach $140.46 billion in 2025 (Statista, 2025c). This competitive environment has driven accelerators to refine their program structures to include features such as structured learning, robust investor networks, and startup grants to attract both top-tier ventures and equity investors

(Lerner and Nanda, 2020).

In contrast, Latin America and South Asia represent emerging accelerator markets with significantly less developed capital ecosystems (Shetty et al., 2020). Seed-stage VC investment is projected at only $9.46 billion and $2.57 billion, respectively, for 2025 (Statista, 2025a,b). These ecosystems face fundamental challenges, including limited investor presence, weak financial infrastructure, inexperienced managers, and institutional voids (Gonzalez-Uribe and Leatherbee, 2018; Shetty et al., 2020; Uhm et al., 2018). As a result, accelerators in these regions focus on providing basic entrepreneurial support, including idea validation, product development, and access to early markets (Crișan et al., 2021). Additionally, program designs may be tailored to address local socio-economic development priorities, such as fostering social innovation and sustainability in South Asia through impact-focused initiatives (Roberts and Lall, 2019).

The literature also recognizes the diversity in accelerators' structures and programs (Bergman and McMullen, 2022; Crișan et al., 2021; Hallen et al., 2020), recognizing that differences between accelerators may significantly influence differences in new ventures' performance (Chan et al., 2020). Bergman and McMullen (2022) deviate from a simplistic provisional accelerator-startup interaction to "an ever-changing, bi-directional relationship between entrepreneurs and accelerator, with this core relationship informed and influenced by other relations each party maintains" (p.703). Given that startups and accelerators in divergent entrepreneurial ecosystems have different needs and divergent relationships with third-party resources, e.g., investors (Shetty et al., 2020), the accelerator design will be adjusted according to the most pressing needs of the startups and the environment they operate in. As a result, more or less emphasis will be put on the main role the accelerator plays as a support system, depending on the ecosystem and the region. Whether the focus is on the validation of ideas, the provision of learning and product development, the accessibility to the market and growth, or support for innovation (Crișan et al., 2021), it will depend on the necessity within the given market (Shetty et al., 2020).

Taken together, these insights underscore the importance of both regional context and accelerator design in shaping early-stage financing outcomes. While accelerator participation generally facilitates access to equity investment, the specific conditions necessary for success may vary across ecosystems. As a result, we hypothesize that:

Hypothesis H1 *There are regional differences concerning the necessary accelerator design features for obtaining external equity investments.*

4.2.4 Program features in established markets

The accelerator program structural design elements are divided into two overarching categories: program package features and program setting features (Kramer et al., 2023; Pauwels et al., 2016). Literature emphasizing learning effects, knowledge spillovers, and accelerators' organizational design (Cohen et al., 2019b; Piezunka et al., 2022; Posen and Chen, 2013; Winston Smith et al., 2015), suggests that diversity in accelerator structure may drive variation in observed impact on post-accelerated new venture performance.

4.2.4.1 Program package features - North America

Program package features represent the core content components of North American accelerators' programs, entailing accelerator grants, structured curriculum, and demo days. Given that early-stage ventures' entrepreneurs face significant challenges: high liability of newness (Bruderl and Schussler, 1990; Stinchcombe, 1965), uncertainty (McKelvie et al., 2011; Mousavi and Gigerenzer, 2014), and resource scarcity (Gupta et al., 2006; Lee and Lévesque, 2023), these features are designed and assumed to help entrepreneurs overcome these challenges. As venture capital investors' exposure to risk increases non-linearly with investment size (Ansar et al., 2017), they especially might be interested in accelerator programs that include such features when making high-equity investments. In other words, larger investments amplify the potential downside of startup failure, making risk mitigation mechanisms essential.

Prior studies suggest that accelerator grants, though typically small, serve a dual function: (1) help bridge early-stage funding gaps, allowing startups to focus on product development and scaling (Cohen, 2013; Cohen et al., 2019b), and (2) serve as a signal of quality, reducing investor uncertainty and increasing the likelihood of follow-on equity investments (Cohen et al., 2019b; Kleinert et al., 2020). This signaling becomes especially important in the context of large VC investments, where the downside risk of startup failure is heightened. Specifically, accelerators' willingness to provide seed capital signals "skin in the game", demonstrating their commitment and belief in the potential of selected startups (Frid et al., 2015; Jia and Wang, 2017). In the context of high-equity stakes, this commitment by the ac-

celerator is seen as a critical precondition for external capital, reducing information asymmetries and uncertainty (Kleinert et al., 2020). Furthermore, in mentor-based accelerator programs, grants raise the stakes for mentors, program directors, and founders, motivating them to deliver higher-quality, more actionable feedback (Assenova and Amit, 2024; Cohen et al., 2019a,b). In contrast, for smaller investments, the need for such signaling is reduced, and investors may be willing to tolerate greater ambiguity given the lower exposure and transaction costs.

Hypothesis H2a *An accelerator program providing the opportunity for an accelerator grant is a necessary condition for high equity investments in North America.*

A structured curriculum provides early-stage ventures with formal education, critical resources, and knowledge designed to address the mentioned challenges in venture development, helping entrepreneurs refine strategies and enhance innovation (Cohen et al., 2019a,b; Hallen et al., 2020). Unlike informal learning, where entrepreneurs individually seek knowledge, structured education offers a standardized cohort-wide lesson plan that ensures that all participants gain foundational competencies (Assenova and Amit, 2024; Cohen et al., 2019b; Gonzalez-Uribe and Leatherbee, 2018). According to bounded rationality theory, even experienced founders suffer from cognitive limitations and often make decisions based on incomplete or biased information (Cohen et al., 2019a; Hallen et al., 2020). As "cognitive misers," they may rely on heuristics and exhibit confirmation bias, overweighting familiar views while ignoring contradictory evidence (Cohen et al., 2019a). Structured curricula are explicitly designed to surface and counteract these biases, equipping entrepreneurs with tools to make better strategic decisions and adapt to dynamic markets (García-Ochoa et al., 2021). This structured, bias-reducing support is particularly critical when venture capitalists (VCs) consider large equity investments. Larger investments magnify downside risks and therefore require more rigorous risk mitigation. Formal educational programming demonstrates that the startup has undergone systematic preparation, enhancing its innovation capacity and decision quality (Cohen et al., 2019b; Gonzalez-Uribe and Leatherbee, 2018). By contrast, when smaller investments are at stake, the cost of implementing or requiring such structured programs may not be justifiable, as VCs face lower exposure and can rely on leaner due diligence methods.

Hypothesis H2b *An accelerator program having a structured curriculum is a necessary condition for high equity investments in North America.*

Demo days enhance early-stage ventures' visibility and create networking opportunities with potential investors, such as venture capitalists and business angels, while also fostering learning for future investment rounds (Assenova and Amit, 2024; Clark, 2008; Cohen, 2013; Hochberg, 2016). These events not only signal credibility, reinforced by the accelerator's reputation, but also serve as developmental milestones, helping entrepreneurs refine their pitches and improve their ventures (Assenova and Amit, 2024; Clark, 2008; Cohen, 2013; Gonzalez-Uribe and Leatherbee, 2018; Hochberg, 2016; Yu, 2020).

In mature ecosystems like North America, demo days may be particularly valuable for positioning startups competitively in equity markets (Uhm et al., 2018). Given that demo days require early-stage investor involvement, they likely represent an important factor in attracting higher levels of investment due to visibility and credibility mechanisms. In lower-investment situations, however, these formal mechanisms may be bypassed in favor of more direct or informal channels, where the expected return just does not warrant a large due diligence or visibility effort.

Hypothesis H2c *An accelerator program having demo days is a necessary condition for high equity investments in North America.*

4.2.4.2 Program setting features – North America

The program setting features encompass the broader environment of the accelerator's program setting, entailing sector focus, impact focus, and program duration.

Sector focus allows accelerators to cater specifically to startups within particular industries, providing access to specialized resources, targeted mentorship, and networking opportunities tailored to address sector-specific challenges (Assenova and Amit, 2024). Further, recent studies indicate that there are potentially variations concerning the signal credibility of accelerator participation, based on different industries (Browne et al., 2024), and that venture capital can specialize or diversify (Gompers et al., 2009; Norton and Tenenbaum, 1993) when investing in early-stage ventures in certain industries.

A longer program duration allows startups to refine business models, iterate on product development, and engage in deeper mentorship, particularly when additional time is needed to build expertise and adapt to market constraints (Assenova and Amit, 2024; Cohen et al., 2019b). By extending accelerator benefits over a longer period, accelerators can provide sustained support, fostering the development of more robust early-stage ventures.

An impact focus is particularly relevant in entrepreneurial ecosystems shaped by socio-economic challenges, where access to equity investments, venture capital networks, and mentorship is limited (Uhm et al., 2018).

Although sector focus, program duration, and impact focus appear to be beneficial in North America, the literature does not imply that these individual features are necessary conditions, but rather highlight the supportive nature of these features, which become relevant in combination with the core program features in attracting high equity investments.

4.2.5 Program features in emerging markets

While considerable research has examined the overall impact of accelerator participation on startup performance, much less attention has been given to identifying which specific accelerator design features are key in emerging market contexts. Given the limited and sometimes contradictory findings in existing literature, this study focuses on the key accelerator design features that have emerged as prominent within the region-specific research on emerging markets. We focus on the key expected necessary condition in Latin America and South Asia, and argue for the regions independently as their institutions and subsequently their venture capital market are significantly divergent (Bruton et al., 2009), which also implies divergent needs in their accelerators.

4.2.5.1 Latin America

While learning is a central pillar of accelerator program design (Hallen et al., 2020), the form and function of learning mechanisms vary across regional contexts. In Latin America, a structured curriculum, comprising formal, cohort-based entrepreneurial education, is likely a necessary condition for securing high levels of equity investment. Gonzalez-Uribe and Leatherbee (2018), in their study of Chile, found that basic services such as seed capital or shared office space had little impact on startup outcomes unless combined with entrepreneurial schooling. This suggests that in Latin American ecosystems, where institutional voids limit access to market-specific knowledge, structured education serves as a foundational input to venture development. Similarly, Goswami et al. (2018) highlight the need for teaching the 'basics' of entrepreneurship in a structured educational program in Bangalore-based accelerators. Roberts and Lall (2019) further support this argument in their analysis of Mexican accelerators, highlighting that many founders in Mexico enter accelerators

with limited exposure to structured entrepreneurial education and lack familiarity with investor expectations. As a result, accelerators in Mexico place significant emphasis on developing business fundamentals and strategic skills through formal instruction. In such contexts, a structured curriculum does not merely complement other features; it fills a critical gap by equipping founders with the cognitive tools and strategic frameworks required to attract and manage external capital. Where informal mentoring networks may be underdeveloped or inconsistently available, formal education becomes a vital substitute for acquiring investor-relevant knowledge. Moreover, as Seet et al. (2018) argues that formal learning must extend beyond "know-what" and "know-how" to also develop "know-who," enabling entrepreneurs to interact effectively with investors and reduce information asymmetries.

A formal curriculum supplies standardized investor-relevant knowledge and skills (market-readiness, pitch refinement, financial literacy) that informal mentoring alone may not reliably deliver across cohorts. From a theoretical perspective, structured curriculum could reduce information asymmetries and strengthens signaling in two ways: (1) it might improve venture quality ex ante, enhancing human capital, strategic framing, and operational readiness that investors value (bounded rationality and learning theory; Cohen et al., 2019a; García-Ochoa et al., 2021; Hallen et al., 2020; Simon, 1957), and (2) it might serve as a credible, observable signal of systematic preparation that investors can use to screen entrants (signaling theory; Cohen et al., 2019b; Lerner, 1999; Spence, 1973). These mechanisms matter more for large equity commitments because bigger investments amplify downside risk and thus raise investors' demands for verifiable signals and demonstrable preparedness (Ansar et al., 2017). In contrast, for smaller investments, the investor's exposure is lower and less rigorous, so formal schooling may be beneficial but not essential. Hence, in the emerging market contexts, where institutional voids and uneven mentor pools limit informal learning, the structured curriculum functions not merely as an enhancement but as a foundational prerequisite for attracting substantial BA/VC equity. Therefore, we hypothesize:

Hypothesis H3 *An accelerator program having a structured curriculum is a necessary condition for achieving high equity investments in Latin America.*

4.2.5.2 South Asia

An impact focus is particularly relevant in entrepreneurial ecosystems shaped by socio-economic challenges, where access to equity investments, venture capital net-

works, and mentorship is limited (Roberts and Lall, 2019; Uhm et al., 2018). In emerging markets, there is an increasing demand for investments that deliver financial capital while also addressing critical social and environmental challenges (Lerner et al., 2016), with India emerging as one of the largest marketplaces for social venture investing (Rajan et al., 2014). Impact-driven accelerators help bridge these gaps by connecting startups with mission-driven investors and philanthropic organizations, facilitating investment in ventures that address critical development priorities (Roberts and Lall, 2019). In rural India, Simpa Networks developed a solar offering service model that provides the poorest Indian households with essential clean, safe, and reliable electricity (Roberts and Lall, 2019). Thus, a strong impact-oriented focus for accelerators in South Asia (mainly India) might be necessary to address regional development priorities and socio-economic challenges, which are at the core of mission-driven investors. In such contexts, an impact-oriented approach may not only be beneficial but also necessary to attract funding and drive sustainable startup growth. Aggarwal and Elembilassery (2018) show that in India, VC funds view impact-oriented investment opportunities with skepticism when social metrics and regulatory frameworks are poorly standardized, implying that accelerators with a strong impact focus (and credible measurement) help reduce that ambiguity, thus becoming more necessary for large equity commitments when rigorous due diligence processes are applied. As a result, we propose the following hypothesis:

Hypothesis H4 *An accelerator program having an impact focus is a necessary condition for achieving high equity investments in South Asia.*

4.3 DATA AND METHOD

4.3.1 Data

We utilized open-source data from the Entrepreneurship Database Program at Emory University, supported by Global Accelerator Learning Initiative (GALI), which has information on 23,364 early-stage ventures that applied to 408 enterprise accelerator programs worldwide, from 2013 to 2019. In line with this study's focus, we applied the following sampling criteria: for-profit early-stage ventures, first-time accelerator-participants, first-time early-stage investment (e.g., business angels/venture capital) receivers, and younger than 7 years when applying for the

accelerator program. This resulted in an initial sample of 395 accelerators and, overall, 13,673 early-stage ventures, with average age at application for the accelerator program being 1.75 years. Based on availability and divergence in entrepreneurial ecosystem, we focused on three regions and considered only early-stage ventures that have their headquarters and mainly operate in the region where they applied for the accelerator program[4], resulting in 2,474 early-stage ventures and 105 accelerators in North America (NA)[5]; 3,602 early-stage ventures and 108 accelerators in Latin America (LA)[6]; 1,304 early-stage ventures and 28 accelerators in South Asia (SA)[7]. In line with the focus of our study on post-acceleration performance, we removed the unsuccessful accelerator applicants, decreasing the sample size to 443 startups and 96 accelerators (NA), 809 startups and 101 accelerators (LA), 141 startups and 26 accelerators (SA). After removing the missing values on our focal variables (e.g., program design features, early-stage investment amounts by business angels and venture capital)[8,9], resulting in final sample of 199 startups and 70 accelerators in NA, (2) 367 startups and 79 accelerators from LA, and (3) 66 startups and 22 accelerators from SA. After aggregating the financial data from the early-stage ventures linked to a specific accelerator, our main analysis is conducted on the accelerator level.

[4] We aim to assess the varying impact of accelerators across different regions. However, including accelerators located in regions different from their participating ventures could distort these effects. To keep the sample as straightforward as possible, we therefore impose this restriction. Since NCA does not allow for control variables and is sensitive to outliers, careful sample selection is crucial. Accordingly, we restrict the sample to our focal population.

[5] *USA and Canada.*

[6] *Antigua and Barbuda, Argentina, Barbados, Bolivia, Brazil, Chile, Colombia, Costa Rica, Curaçao, Dominica, Dominican Republic, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Haiti, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Puerto Rico, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Uruguay, Venezuela.*

[7] *India, Bangladesh, Nepal, Singapore.*

[8] In our additional analysis and robustness test, we considered all types of equity investments. Types of external equity investments: founder's friends or family members, banks, non-bank financial institutions, angel investors, other companies, government agencies, venture capitalists, foundations or nonprofits, accelerators, business plan competitions, crowd-fund campaigns, employees, or other individuals. Then the sample size is 223 startups and 72 accelerators (NA), 387 startups and 81 accelerators (LA), and 74 startups and 23 accelerators (SA).

[9] We remove an outlier due to data mistake, this accelerator maximum was unrealistically high (20,190,382 dollars versus second highest amount 1,400,000), no investments from BA and VC, founding year same year as application year, and due to the other answers in the survey, appears to be a data mistake.

4.3.2 Variables

The outcome variable (Y) is the maximum amount of external equity investments early-stage venture in the accelerator's portfolio received in the year after accelerator participation from a business angel or venture capital in dollars. This is in line with the focus of our study to learn from unusual data points or patterns (Freedman, 2008; Ruef and Birkhead, 2024). We use equity investment as our outcome variable because it reflects a startup's high future potential. Venture capital investment not only provides financial resources but also signals a firm's growth prospects, serving as a certification that the startup has passed rigorous evaluation and is deemed credible by external stakeholders (Davila et al., 2003; Kaplan and Strömberg, 2004; Kleinert et al., 2020; Svetek, 2022). Empirical evidence shows that VC-backed startups achieve superior outcomes in sales, employment, and market penetration, establishing VC funding as a strong indicator of scalable, high-growth ventures (e.g., Bertoni et al., 2011; Colombo and Grilli, 2005; Colombo et al., 2010; Gompers et al., 2020).

The independent variable (X), or in other words, the conditions, are the accelerator program design features, which are mostly dummy variables. Accelerator grant implies that the accelerator offers the possibility of grants or investments provided by the accelerator, however, this grant does not have to be guaranteed for all program participants. Other design features are whether the accelerator has an explicit impact area focus or an explicit sector focus. A wide variety of impact areas are taken into consideration in the GALI dataset.[10] Curriculum indicates whether the program has distributed a structured curriculum to participants in written or electronic form. Demo days specify whether the program features pitch nights or demo days that connect participants with potential investors. Lastly, the program duration is a categorical variable that takes values: 1 - when the program is shorter than 3 months, 2 - when the program lasts between 3 and 6 months, and 3 - when the program is longer than 6 months.

[10] Access to clean water, access to education, access to energy, access to financial services, access to information, affordable housing, agriculture productivity, biodiversity conservation, capacity building, community development, conflict resolution, disease-specific prevention and mitigation, employment generation, energy and fuel efficiency, equality and empowerment, food security, generate funds for charitable giving, health improvement, human rights protection or expansion, income/productivity growth, natural resources conservation, natural resources/biodiversity, pollution prevention and waste management, sustainable energy/fuel efficiency, sustainable energy, sustainable land use, support for high-impact entrepreneurs, water resources management, support for women and girls.

4.3.3 Empirical analysis

Necessary Condition Analysis (NCA) is a research method used to identify variables that are necessary but not sufficient for an outcome to occur (Dul, 2016b, 2020, 2021). In NCA, the focus is on detecting whether the absence of a specific condition guarantees the absence of a desired outcome. This method is widely applicable in various fields, such as social sciences, management, and healthcare. It can be used as a standalone method or as a complement to traditional methods by emphasizing the significance of critical conditions that must be present, offering a unique way to explore complex (causal) relationships and improve predictive accuracy. Unlike additive models, where variables can compensate for one another to achieve an outcome, the necessity logic implies that a necessary condition cannot be offset by higher values in other variables. Note that this does not imply sufficiency; the presence of the condition does not implicitly lead to the presence of the outcome. As an example, being registered for a course is a necessary condition to be able to pass the course's exam. However, it is not a sufficient condition, because just being registered does not imply that you will pass the course (you will also have to study for it).

NCA is applied by identifying conditions essential for achieving specific outcomes. In this method, scatter plots represent individual values that help visualize the relationship between a condition and an outcome, highlighting zones where the outcome cannot occur without a particular condition (Dul, 2016b, 2020, 2021). NCA defines the boundary between the presence and absence of cases in the XY-plane, referring to this boundary as the "ceiling". Cases exist on or below this ceiling, but not above it. The ceiling shows that for a given level of X, values of Y can be less than or equal to the ceiling, but cannot exceed it. This implies that X is necessary for Y to occur. The ceiling illustrates the limiting effect of X on Y, meaning that without a certain level of X, achieving a certain level of Y is impossible. This empty space above the ceiling line is called the ceiling zone and can often be found in the upper left corner. The basic mathematical equation thus is (Dul, 2016b, p.21):

$$Y \leq f(X) \tag{4.1}$$

with f(X) the ceiling function.

There are two default ceiling lines: the Ceiling Envelopment with Free Disposal Hull (CE-FDH) and the Ceiling Regression with Free Disposal Hull (CR-FDH) technique (Dul, 2016b, 2020, 2021). The former (CE-FDH) represents a step function,

making it suitable when either X or Y consists of discrete values with a limited number of levels, or when the boundary of the distribution is irregular. The latter (CR-FDH) represents a straight trend line that connects the upper-left corner points of the CE-FDH line. Given that most of our conditions are dummies and program duration is a categorical variable (Dul, 2016b, 2021), we focus on the CE-FDH technique.

Components used in NCA to analyze the necessity are: the effect size, its p-value, and the bottleneck. First, the effect size in NCA quantifies the strength of the necessity of a condition; the larger the ceiling zone, the stronger the effect. Therefore, the effect size of a necessary condition can be expressed as the proportion of the ceiling zone relative to the total area where observations are possible (Dul, 2016b). In other words, the effect size (d) can be calculated by dividing the ceiling zone by the scope (Dul, 2016b, p.29):

$$d = \frac{C}{S} \tag{4.2}$$

Where C is the size of the ceiling zone, S is the size of the scope, and d is the effect size. The scope is defined as the potential area with observations, and can be based on either theoretical values or empirically observed minimum and maximum values for X and Y (Dul, 2016b).

As a result, the effect size can take values from 0 to 1. The general benchmark for assessing the necessary condition effect size can be categorized as follows: "small effect" ($0 < d < 0.1$), "medium effect" ($0.1 \leq d < 0.3$), "large effect" ($0.3 \leq d < 0.5$), and "very large effect" ($d \geq 0.5$) (Dul, 2016a,b). Second, the statistical test of NCA is a permutation test to estimate the p-value of the effect size with generally 10,000 permutations to keep the optimal balance between accuracy and efficiency (Dul et al., 2023, 2020). Lastly, the interpretation of NCA analysis can be helped with a bottleneck table that provides a practical guide, listing the threshold levels of conditions required to reach various outcome levels. Together, these elements guide the interpretation of necessary conditions and their impact on outcomes. In contrast to a single bivariate analysis, multiple bivariate NCA allows for several conditions to be analyzed simultaneously.

4.3.4 NCA versus fsQCA

Developed by Ragin (1987, 2008), the Qualitative Comparative Analysis (QCA) method's main goal is not to identify single necessary conditions, as it is in NCA,

but to utilize these conditions as crucial elements to identify complex relationships between multiple factors that lead to a sufficient outcome (Schneider and Wagemann, 2012). While NCA can operate with the typical variable scores, such as dummies, categorical, and continuous variables, fsQCA depends on membership scores. Fuzzy sets allow researchers to assign partial membership values within a range from 0 (non-membership) to 1 (full membership), while preserving fundamental set-theoretic principles, such as the subset relationship (Schneider and Wagemann, 2012). The key difference in identifying necessary conditions in NCA and fsQCA is the analytical approach and the level of necessity, 'in kind' versus 'in degree' (Dul, 2016a; Vis and Dul, 2018). In NCA, the ceiling line follows the largest observations of Y for each X. This ceiling is used to calculate the empty space that defines necessity. While necessity in fsQCA is based on the diagonal reference line and measures the extent to which the cases are not above the diagonal line, present in the 'empty zone'. In contrast to NCA, fsQCA allows some "deviant cases" above the diagonal as long as the consistency level is above the consistency standard of 0.9 (Dul, 2016a, 2021; Ragin, 2008; Schneider and Wagemann, 2012; Vis and Dul, 2018). Both NCA and fsQCA detect necessity 'in kind' which indicates the presence (or absence) of X is necessary for the presence (or absence) of Y. However, for NCA this is defined by the effect size, its p-value, and the ceiling accuracy, while for fsQCA this is through the necessity consistency and coverage. NCA can provide a more detailed necessity analysis by providing necessity 'in degree', which means a certain level of X is necessary for a certain level of Y. This is not possible in an fsQCA analysis. Although fsQCA is less likely to pick up on necessary conditions that are more nuanced (e.g. necessity in degree), this method's analytic approach allows for a different view on the necessity analysis, and might pick up on conditions that are inconclusive in NCA due to an outlier but are consistent in fsQCA (consistency $>$ 0.9). As a result, fsQCA is less equipped to detect necessary conditions; however, it can still strengthen and substantiate the NCA findings.

4.4 RESULTS

4.4.1 Descriptives

Table 4.1 displays the descriptive statistics with the maximum equity investment (in $) of the best startup in an accelerator's portfolio received by a BA or VC, as an outcome variable for all three regions, North America, Latin America, and

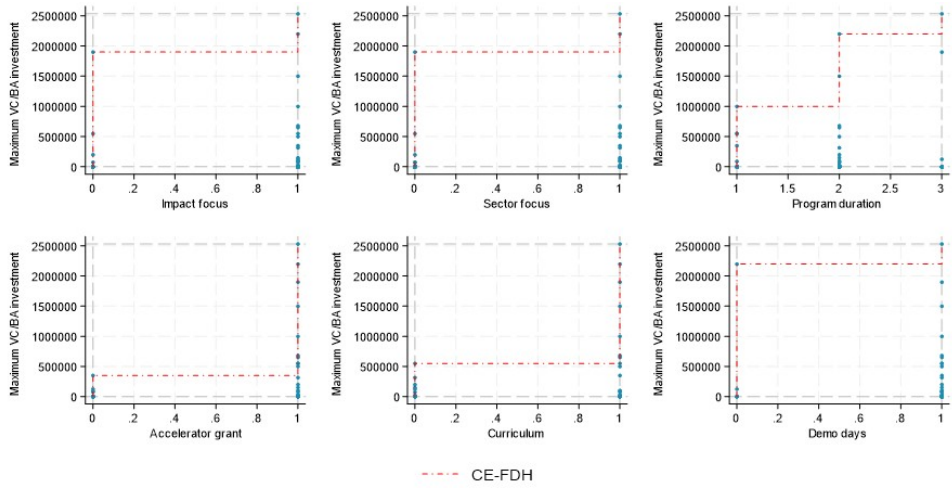
South Asia. The distribution of equity investments is highly skewed, meaning that there are many accelerators with zero equity investment or relatively low investment levels in comparison to a few outliers that are exceptionally well-performing firms with extremely high equity investments.[11]

Table 4.1: Descriptive statistics

	Count	Mean	SD	Min	50th percentile	95th percentile	Max
North America							
Equity	70	194657.143	504108.767	0	0	1500000	2533000
Impact focus	70	0.586	0.496	0	1	1	1
Sector focus	70	0.557	0.500	0	1	1	1
Program duration	70	1.857	0.666	1	2	3	3
Accelerator grant	70	0.686	0.468	0	1	1	1
Curriculum	70	0.714	0.455	0	1	1	1
Demo days	70	0.914	0.282	0	1	1	1
Latin America							
Equity	79	43198.798	175233.254	0	0	300000	1400000
Impact focus	79	0.405	0.494	0	0	1	1
Sector focus	79	0.367	0.485	0	0	1	1
Program duration	79	2.076	0.813	1	2	3	3
Accelerator grant	79	0.342	0.477	0	0	1	1
Curriculum	79	0.835	0.373	0	1	1	1
Demo days	79	0.696	0.463	0	1	1	1
South Asia							
Equity	22	61409.091	105767.336	0	0	200000	450000
Impact focus	22	0.864	0.351	0	1	1	1
Sector focus	22	0.727	0.456	0	1	1	1
Program duration	22	1.955	0.844	1	2	3	3
Accelerator grant	22	0.727	0.456	0	1	1	1
Curriculum	22	0.500	0.512	0	0.5	1	1
Demo days	22	0.864	0.351	0	1	1	1

[11] This paper focuses on accelerated startups and the within-difference of accelerators. However, we provide additional descriptive analyses to adhere to the broader studies of accelerators in which non-accelerated and accelerated startups are compared, and show that there is selection into accelerated programs, but that controlling for this accelerated startups still perform better in line with the literature (e.g., Gonzalez-Uribe and Leatherbee, 2018; González-Uribe and Reyes, 2021; Hallen et al., 2020; Venâncio and Jorge, 2022). Further explanation can be found in the Appendix in subsection C.2 and Tables C5 and C6.

Figure 4.1: Scatter plots necessary conditions for max equity investments in North America



4.4.2 NCA analysis

4.4.2.1 NCA - North America

Figure 4.1 represents the six individual scatter plots for impact focus, sector focus, program duration, accelerator grant, curriculum, and demo days, in the North American sample. The most important conditions appear to be having the possibility of obtaining an accelerator grant and having a structured curriculum. Due to the results being driven by exceptionally high-performing startups with a wide disparity in the top equity investment amounts (outliers), the effect sizes are considerably large. However, these effect sizes can indicate a ranking of the importance of each condition.

Table 4.2 shows the effect sizes and p-values of the accelerator program design conditions for divergent samples. Our main model is displayed in column (1)[12]. Although all effect sizes are above 0.1 and thus could potentially indicate a necessary effect from certain levels of BA/VC equity investments, we only find a significant necessary condition for the accelerator offering the possibility of obtaining an accelerator grant with an effect size of 0.86 ($p < 0.05$). Secondly, having a structured curriculum is necessary at the 10% level ($p < 0.1$). A bottleneck table would illustrate that for equity investments above 350,000 dollars, it becomes necessary for the

[12]corresponding to the scatter plots in Figure 4.1

accelerator to offer the possibility of accelerator grants. In other words, accelerator grants become important for the top 15 percent of accelerators in the sample. Although significant at 10%, having a structured curriculum would become necessary for equity amounts above 550,000 dollars and thus crucial for the top 9 percent of accelerators. As a result, we confirm hypothesis H2a, but cannot fully confirm hypothesis H2b due to the 10% significance level.

These results highlight the contribution of the NCA analysis, its ability to detect necessity in degree. For lower equity investment levels, there appear to be no necessary conditions. However, for startups to attain exceptionally high equity investments (85th percentile), the accelerator's design needs to have the necessary design elements present.

Table 4.2: Effect sizes and p-values for max equity investments in North America

	Accelerator-level						Firm-level			
	BA or VC equity		All equity		Removed outlier (BA/VC)		BA or VC equity		All equity	
	(1)		(2)		(3)		(4)		(5)	
	d	p	d	p	d	p	d	p	d	p
Impact focus	0.250	0.335	0.250	0.344	0.250	0.573	0.250	0.389	0.250	0.359
Sector focus	0.250	0.310	0.250	0.325	0.250	0.545	0.250	0.302	0.250	0.283
Program duration	0.368	0.137	0.368	0.113	0.507**	0.034	0.368	0.161	0.368	0.162
Accelerator grant	0.862**	0.016	0.862***	0.009	0.862**	0.026	0.862**	0.019	0.862**	0.012
Curriculum	0.783*	0.083	0.783*	0.095	0.783	0.113	0.783*	0.089	0.783*	0.082
Demo days	0.131	0.915	0.131	0.898	0.951	0.346	0.131	0.903	0.131	0.901
Sample size	70		72		69		199		223	

Note: d = effect size, p = p-value. $***p < .01; **p < .05; *p < .10$. The sample size between the BA/VC versus all equity can diverge because we do not take the firms that have equity from a different type into account. In other words, we do not interpret their value as 0 for only receiving BA or VC investment equity. Since we leave these observations out, it might reduce the number of accelerators if there is no information regarding equity for the other startups in their portfolio.

To extend the main findings, multiple alterations are considered. First, we include considering maximum equity amounts from all possible sources[13] of the best startup in an accelerator, not only from business angels or venture capital, as shown in column (2). Secondly, we change the level of analysis from accelerator to firm level and look at the maximum equity investments for each firm. This results in an analysis only including BA and VC investments in column (4) and an analysis

[13]founder's friends or family members, banks, non-bank financial institutions, angel investors, other companies, government agencies, venture capitalists, foundations or nonprofits, accelerators, business plan competitions, crowd-fund campaigns, employees, or other individuals

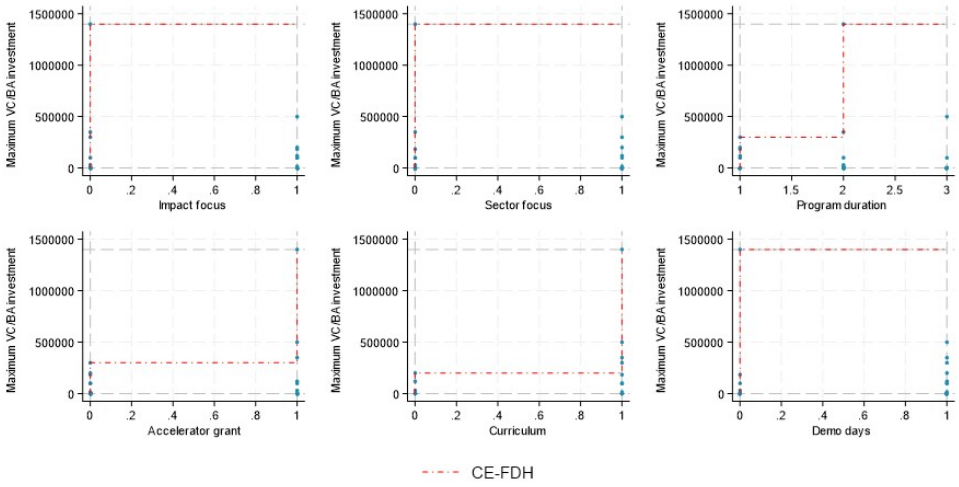
including all equity investments in column (5). These analyses indicate that the results are robust considering more equity investment types and changing the level of analysis to the individual firm level.

Lastly, in the main analysis, the results for demo days have a small effect size which is due to a single outlier that is more than 17 times larger compared to the second largest observation for the absence of demo days ($2,200,000 compared to $125,000), as can be seen in the scatterplot in Figure 4.1. Therefore, a last additional analysis removes this outlier and results in an effect size of 0.951 for demo days (column (3), Table 4.2), which would position the condition as the most important necessary condition with a bottleneck at 125,000 dollars. However, the p-value in this scenario would still be too high, and NCA cannot claim statistical necessity. This, however, is most likely caused by a skewed distribution of demo days. Since most accelerators in North America have demo days, only a few (5 in this sample) do not offer demo days. Given the small sample size and the skewed distribution, it is not possible to statistically test the necessity of the condition (Dul, 2024). Although we cannot confirm hypothesis H2c based on the NCA results, they give cause to further investigate the necessity of demo days in North American accelerators.

Additional robustness tests can be found in Table C1 in the appendix. Taking a worldwide sample, the effect sizes are the same as for the North American sample. This is in line with expectations, as North America's VC and BA ecosystems are the most developed and thus are expected to invest the largest equity amounts. Moreover, the main analysis is run with the equity amounts larger than zero. The results are robust. However, the worldwide analysis (column 1) shows that having a curriculum is significant at 5% instead of 10% ($p<0.05$). Similar decrease in p-value and increase in significance of curriculum for the sample of North America without the zero equity amounts (column 3).

In conclusion, in North American accelerator programs, the possibility of offering accelerator grants is the most critical condition, becoming necessary for the top 15% of accelerators and their startups, which are considered to have high potential and thus receive considerably higher equity investments from business angels or venture capitalists. Providing a structured curriculum appears to be essential for the top 9% of accelerators (and their highest performing startup). However, the results are not robust considering the significance level and are only significant at 10% in the main analysis.

Figure 4.2: Scatter plots necessary conditions for max equity investments in Latin America



4.4.2.2 NCA - Latin America

The scatter plots indicate that having a structured curriculum and opportunity for accelerator grants are the most important conditions (Figure 4.2), similar to the North American sample. However, contrary to North America, the structured curriculum appears to be the most important condition. Impact focus, sector focus, and demo days are not necessary conditions for achieving high BA or VC equity investments. The results for these design features are not robust, removing one or two observations at the top (highest equity values) could reverse the necessity effect. As shown in Table 4.2, column (1), the effect sizes for curriculum (0.86) and accelerator grant (0.79) are the largest. However, we only find a significant p-value for accelerator grants ($p < 0.05$). Thus, for investment values above 300,000 dollars, providing opportunities for accelerator grants becomes a bottleneck preventing accelerated firms from achieving higher BA or VC equity investments and belonging to the top 4 percent performing accelerators (96.15th percentile). As a result, we see indications that having a structured curriculum could be a key necessary condition in Latin America, but we cannot confirm hypothesis H3, as we do not find a statistically significant effect. Similar to North America, the accelerator grant feature is a necessary condition at the higher levels of BA and VC investments. However, for lower amounts of equity investment, there are no necessary conditions.

Table 4.3: Effect sizes and p-values for max equity investments in Latin America

	Accelerator-level				Firm-level			
	BA or VC equity		All equity		BA or VC equity		All equity	
	(1)		(2)		(3)		(4)	
	d	p	d	p	d	p	d	p
Impact focus	0	1	0	1	0	1	0	1
Sector focus	0	1	0	1	0	1	0	1
Program duration	0.393	0.534	0.392	0.482	0.393	0.579	0.393	0.540
Accelerator grant	0.786**	0.038	0.429	0.358	0.786**	0.013	0.429	0.346
Curriculum	0.857	0.465	0.857	0.385	0.857	0.563	0.857	0.492
Demo days	0	1	0	1	0	1	0	1
Sample size	79		81		367		387	

Note: d = effect size, p = p-value. ***$p < .01$; **$p < .05$; *$p < .10$.

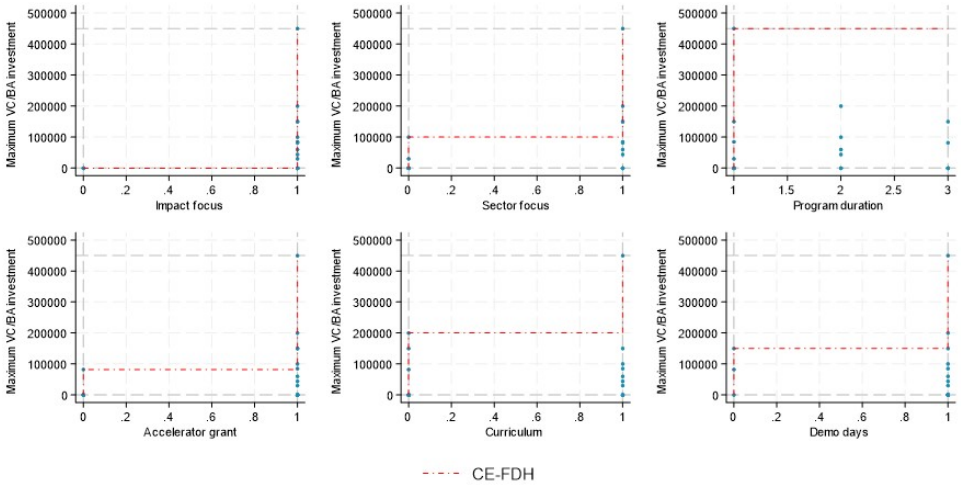
Regarding the extensions, these results appear to be robust when changing to a firm-level setup (column 3). This does not hold when other types of equity investments are taken into consideration (columns 2 and 4). Indicating that the accelerator grant is only necessary in case of high BA and VC investments, not when other investment types are in play. This is in contrast to North America, in which an accelerator grant is dominant for all types of investors.[14]

4.4.2.3 NCA - South Asia

Figure 4.3 shows the scatter plots for the design features for South Asia. Although having a curriculum appears to have a considerable effect size, it is based on a single outlier when the condition is present. Thus, we do not find a robust necessity for having a structured curriculum in South Asia. Additionally, program duration does not appear to be relevant in attaining higher equity amounts from business angels or venture capital in South Asian accelerators.

[14]In Latin America's venture capital markets, where investor networks are still maturing and investment volumes remain modest, other equity mechanisms, such as friends and family, local informal investors, and government programs, might provide funding amounts in a similar range to early-stage venture capital and business angel investments. In Latin America, over half of the population relies on loans from family and friends due to limited trust in formal financial institutions and easier access to informal credit (Herrero et al., 2025). Informal and public funding channels operate under different logics: friends and family prioritize social ties and support motives (Lee and Persson, 2016; Zhou et al., 2022), while government programs fund innovation and early-stage ventures based on policy goals rather than financial returns (Grilli and Murtinu, 2015; Mazzucato and Semieniuk, 2017). Consequently, their investment decisions depend less on market-based signals, such as accelerator grants, that are highly valued by profit-oriented venture capital and business angel investors (Cohen et al., 2019b; Hsu et al., 2014). As a result, the differences in results regarding all equity between North America and Latin America might be attributed to these dynamics, which could be further examined in future research.

Figure 4.3: Scatter plots necessary conditions for max equity investments in South Asia



The driving factor for BA or VC equity investments appears to be the accelerator having an impact focus. Each accelerator for which their startups received BA or VC equity investments had an impact focus. Table 4.4 shows the effect sizes and corresponding p-values depending on the defined sample. The main results are shown in column (1). Impact focus has an effect size of 1, indicating a necessary condition in kind. In other words, for each investment (>$0), the accelerator needs to have an impact focus. However, in this sample, the results are not significant with a p-value of 0.14. Although the effect size has the maximum value, due to the small sample and the extremely skewed distribution (only 3 zero observations for no impact focus), it is not possible to statistically test the significance of the necessity of the condition (Dul, 2024). When analyzing the maximum BA and VC equity amount on the firm level, which increases the observations, impact focus becomes significant at the 10% level (p = 0.06) (column 3). Adding to this sample all types of equity (column 4), the effect size remains 1, but the p-value becomes significant (p=0.013). This highlights that the insignificance of our main model is due to a lack of statistical power (Dul, 2024). Although all samples have a divergent focus, a clear trend is visible that indicates that impact focus might be a key feature for achieving equity investments of the accelerated firms in the subsequent year. Thus, based on the NCA analysis, we cannot fully confirm hypothesis H4, and require additional analyses.

Table 4.4: Effect sizes and p-values for max equity investments in South Asia

	Accelerator-level				Firm-level			
	BA or VC equity		All equity		BA or VC equity		All equity	
	(1)		(2)		(3)		(4)	
	d	p	d	p	d	p	d	p
Impact focus	1	0.14	1	0.126	1*	0.060	1**	0.013
Sector focus	0.778	0.239	0.778	0.121	0.778	0.157	0.778**	0.050
Program duration	0	1	0	1	0	1	0	1
Accelerator grant	0.818	0.11	0.533	0.697	0.818	0.199	0.533	0.780
Curriculum	0.556	0.495	0.553	0.478	0.556	0.582	0.533	0.591
Demo days	0.667	0.744	0.667	0.547	0.667	0.701	0.667	0.494
Sample size	22		23		66		74	

Regarding the accelerator grant, the effect size (0.818) is high and the p-value is rather low (0.11), given the statistical power, however, remains insignificant (column 1). Additionally, moving to the firm size only reduces the significance of the condition. Similar to Latin America, the accelerator grant becomes less important when taking into account all types of equity investments. Lastly, sector focus has a large effect size (0.778), consistent across all models, and becomes significant ($p < 0.05$) in the largest sample model (column 4). It indicates that sector focus might become a second important accelerator feature; however, to robustly and significantly confirm these findings, further research is necessary.

4.4.3 Extension: necessity with fsQCA

4.4.3.1 Calibrations

The calibration values are selected based on a combination of theory and data (Table C2). Only a small percentage of startups receive equity investments, especially high equity amounts, from business angels or venture capital. This is in line with our data, for which many accelerators did not have startups that received equity investments after participation. Since receiving any type of equity can already be labeled an achievement, the fully-out point is calibrated at 0 and the crossover point at 0.01[15], to signal that any amount above 0 dollars is a present condition. To fully capitalize on the fact that larger amounts of equity investments are highly sought

[15]Due to analytical complexity of fuzzy sets and the exact crossover point (0.5), Ragin (2008) recommends avoiding the exact crossover point (0.5) in calibrations. Similarly to Fiss (2011) who adds a constant of 0.01 to the causal conditions, we subtract 0.01 from the duration as considering a duration longer than 3 months is present and use 0.01 (a penny) as crossover point for equity.

after, we calibrate the "fully out" point at the largest value for equity investment. These calibrations are most consistent with the values of the NCA and thus offer the highest comparability between methods.[16] Given the importance of choosing the calibration values, we introduce additional calibrations for robustness in Table C2.

4.4.3.2 Necessary analysis

Table 4.5 shows the results of the necessary condition analysis of the program features for maximum equity investments by BA and VC per accelerator with fsQCA. The North American sample has one necessary condition, demo days at a consistency of 0.93, while the other design features do not appear to be necessary. Thus, North American accelerators need to feature demo days in their program for startups to receive equity investments in the subsequent year. The fsQCA necessity analysis does not find the necessary conditions found in the NCA analysis, accelerator grant, and to a lesser extent, curriculum, which is to be expected as these necessities are only necessary in degree, at a certain amount of equity. On the other hand, fsQCA finds a necessary condition in kind for demo days, which we cannot find in the NCA analysis. However, the scatterplot concerning demo days in North America in the NCA analysis highlights that most accelerators that receive any amount of equity investment provide demo days in their program. As previously reported, removing the outlier would increase the effect size to 0.951 (see Table 4.2), which is extremely high and would indicate a potential key necessary condition. Given that fsQCA is less strict concerning outliers and handles a 0.9 consistency rate, a single outlier does not alter the results. Thus, the fsQCA necessary condition analysis strengthens and extends the NCA analysis by confirming the necessity in kind of demo days for getting equity investments from BA or VC after accelerator participation, confirming hypothesis H2c. In contrast to the NCA findings for accelerator grants and curriculum, this condition is important for all equity investments and not only the highest amounts. As a result, these results go beyond the expectations that demo days would only be necessary to achieve the high equity investment amounts.

[16] The NCA analysis is run with the same calibrations and membership values in additional robustness tests for exact comparison in Table C4.

Table 4.5: Necessary analysis of program features for max BA/VC equity on accelerator level in fsQCA

	North America		Latin America		South Asia	
	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage
Impact focus	0.745	0.310	0.478	0.182	**0.980**	0.384
Sector focus	0.685	0.299	0.392	0.165	0.811	0.378
Program duration	0.741	0.409	0.685	0.196	0.564	0.395
Accelerator grant	0.792	0.281	0.415	0.187	0.882	0.411
Curriculum	0.732	0.250	0.820	0.151	0.658	0.445
Demo days	**0.902**	0.240	0.685	0.196	0.811	0.318

Note: Consistency $\geq$ (Ragin, 2008; Schneider & Wagemann, 2012)

Concerning Latin America, no necessary conditions in kind are found, as no design features are consistent above 0.9. This is in line with the NCA findings that only find a necessary condition in degree for accelerator grants, and the scatter plots and effect sizes of the other condition do not appear to indicate any 'hidden' necessary conditions in kind.

Lastly, concerning the South Asian sample, impact focus is a necessary condition in kind with a consistency of 0.98. Although not significant due to statistical restrictions with NCA for this small sample size, the fsQCA and NCA results align. Both the NCA and fsQCA analyses find extremely high values, effect size (1), and consistency level (0.98), hinting that South Asian accelerators need to have an impact focus for their startup participants to receive BA or VC equity investment the following year, confirming and exceeding hypothesis H4.

In conclusion, the results of the necessary analysis in fsQCA are complementary to the findings in the NCA analysis. Providing evidence for the necessity in kind for demo days in North America and an impact focus for South Asia. In other words, these necessary conditions need to be present in an accelerator for their accelerated startups to receive equity investment funding from business angels or venture capital in the year after participation. These results also clearly highlight the divergent needs in accelerator design programs in different regions, confirming hypothesis H1. These fsQCA necessary condition results are also proven robust with divergent calibration (Table C3 in the appendix).

As the design features variables are calibrated to values between 0 and 1 for the fsQCA analysis, we do an additional robustness test of running the NCA analysis with these calibrated values (Table C4 in the appendix). The results are robust with the earlier NCA findings and robust across different calibrations. A minor

note is the lower effect sizes, but this is to be expected as the absolute disparity between the top equity investments amounts is reduced.

4.5 DISCUSSION AND CONCLUSION

4.5.1 Discussion

This study makes several contributions to the literature on accelerator programs and their role in fostering high-growth startups, with a specific focus on equity investment outcomes.

The primary contribution lies in identifying the design features necessary for achieving the highest equity investments from business angels (BA) and venture capitalists (VCs) in the subsequent year for accelerated startups. Unlike prior studies that broadly emphasize accelerator program features enhancing equity financing opportunities (e.g., Assenova and Amit, 2024; Cohen et al., 2019b), this research focuses specifically on necessary conditions for high-potential startups in accelerators. Our NCA findings reveal that offering grants by accelerators is a necessary condition for achieving high equity investments, particularly among the top 15% of accelerators in the sample in mature ecosystems like North America. While the effect is less pronounced, grant offerings also emerge as a necessary condition in emerging markets such as Latin America for the top 4% of accelerators. This suggests that grants represent a broadly applicable necessary condition across multiple regions, in line with Shetty et al. (2020). The added value from offering accelerator grants becomes a key signal to achieve higher equity investments from BA and VCs (Assenova and Amit, 2024; Cohen et al., 2019b). At a lower significance level, the NCA results indicate that accelerators with a structured curriculum are essential for the top nine percent of accelerators in North America. While not the key necessary condition, our findings support existing literature suggesting that structured learning may promote innovative, higher-quality ideas and enhance the willingness to invest larger sums into accelerated startups (Assenova and Amit, 2024; Cohen et al., 2019b; Gonzalez-Uribe and Leatherbee, 2018; Hallen et al., 2020). In particular, Gonzalez-Uribe and Leatherbee (2018) indicate that a structured curriculum has the largest effect size among the design features in Latin America, underscoring the importance of formal learning and entrepreneurial education in that region. Conversely, in emerging markets where accelerators struggle to access experienced mentors and high-quality educational resources, the effectiveness of formal learning

may be significantly reduced (Uhm et al., 2018). Given that we cannot statistically establish significance for the Latin American sample and observe diminished relevance of this feature in South Asia, future research should explore the relationship between learning effects and high equity investments in top accelerator startups, particularly within specific regional contexts. While prior research has predominantly focused on sufficiency-based approaches (e.g., Assenova and Amit, 2024), our findings reveal that necessity logic offers essential insights into why certain features, such as accelerator grants, are crucial for achieving exceptional equity outcomes. This methodological contribution addresses calls for more nuanced analytical frameworks (Dul, 2020) and clarifies the necessity of specific program features that cannot be compensated for by other factors. By shifting the focus from general accelerator effectiveness to the unique design elements that differentiate top-performing startups, our NCA findings help to fill gaps in the existing literature regarding the variability of post-acceleration outcomes (Bergman and McMullen, 2022).

In our second contribution, we emphasize the importance of necessity at two distinct levels: obtaining any amount of equity investment from BAs or VCs, and securing substantial equity investments from these sources. Our study notably advances the methodological discourse surrounding the integration of NCA and fsQCA in the investigation of necessity. NCA is particularly advantageous as it not only identifies necessary conditions but does so in terms of both degree and kind, being specifically designed for this purpose (Dul, 2016b, 2020). However, we demonstrate the complementarity of NCA and fsQCA, as they effectively complement each other by addressing their respective limitations in our sample. Although initial observations may suggest divergent results between the two methods, a deeper analysis reveals their underlying similarities and complementarity. The NCA results indicate that accelerator grants and a structured curriculum are necessary conditions in degree, applicable only for securing higher equity amounts, and thus relevant primarily to high-potential startups within top-tier accelerators. In contrast, the findings from fsQCA underscore necessary conditions in kind, indicating that demo days in North America and an impact-focused approach are essential for achieving any level of equity investments from BAs and VCs. In mature entrepreneurial ecosystems where the competitive equity market provides a challenge for startups to attract top-tier equity investments (Cohen, 2013; Hochberg, 2016), increasing visibility and attracting the attention of top-tier investors is essential. Given an established relationship between accelerators and equity investors, the accelerator acts as a credible source, and thus pitching events or demo days can act as valuable

signals to increase the probability of equity investments of BAs and VCs (Clark, 2008; Uhm et al., 2018). While in South Asia's socially driven entrepreneurial landscape, startups often address pressing socio-economic challenges, an impact-focused accelerator is essential for attracting mission-driven investors and fostering sustainable ventures (Roberts and Lall, 2019; Uhm et al., 2018).

Our third contribution challenges the "one-size-fits-all" approach to accelerator design. Although the rapid imitation of successful models, such as Y Combinator in North America, is prevalent (Hallen et al., 2020), a simplistic copy-paste strategy for integrating design features may not be the most effective path forward. Our fsQCA findings reveal significant regional variation in the necessity of program features. In North America, demo days emerge as a necessary condition due to their role in signaling quality and increasing visibility in a competitive entrepreneurial ecosystem (Hochberg, 2016). In contrast, South Asia's impact focus reflects the need to address regional socio-economic challenges (Roberts and Lall, 2019). These results emphasize that accelerators must align their designs with local ecosystem demands to maximize effectiveness, supporting the notion of heterogeneity in accelerator programs (Bergman and McMullen, 2022; Crișan et al., 2021).

Finally, this study provides actionable insights for policymakers, accelerator managers, and entrepreneurs by highlighting that accelerators are not homogeneous, certain program designs are better suited to attract equity investments and nurture high-growth startups. While prior research confirms that accelerators contribute to startup success, our findings clarify which specific features are necessary for achieving overall equity outcomes and which additional design elements are critical for securing substantial equity investments. Depending on the objectives of entrepreneurs, managers, or policymakers, a strategic and tailored selection of accelerator design features can be made. The requirements for attracting any amount of venture capital or business angel investments differ from those needed to secure top-tier equity investments and foster the growth of gazelles. Moreover, regional variations play a significant role in shaping these necessary conditions, further dispelling the notion of a one-size-fits-all accelerator model. Policymakers should tailor accelerator programs to ecosystem-specific needs rather than applying broad approaches. For entrepreneurs, this implies that accelerator selection should be a strategic decision. Founders need to align program design features, such as accelerator grants, structured curriculum, demo days, and impact orientation, with their anticipated financing pathways and long-term investment goals, ensuring that program participation strengthens their credibility and readiness for future equity

investors. By identifying necessary conditions for higher equity investments, this study enables more effective, regionally adapted accelerator designs to maximize accelerated startup growth and funding success.

4.5.2 Limitations

This study has several limitations that open avenues for future research. The primary limitation is the relatively small sample size, which restricts the generalizability of the findings. While the results provide initial indications of necessary conditions for securing high equity investments, wider generalizations cannot be claimed. Similar to Van Der Valk et al. (2016), our study primarily illustrates how NCA can offer new insights into accelerator programs and high-potential startups. Future research should validate these findings with larger samples across diverse regions and accelerator types to enhance external validity.

A related limitation is the skewed distribution of accelerator program design features in different regions (e.g., the prevalence of demo days in North America and impact-focused accelerators in South Asia). This uneven distribution may limit the ability of NCA to detect significant necessary conditions across all contexts (Dul, 2024). Additionally, larger effect sizes can still be identified in smaller samples, smaller effect sizes require larger datasets to achieve statistical significance after permutation tests (Dul, 2024). This means that certain program features that may be necessary under specific conditions might not have been fully captured due to the sample constraints. Future studies should address this limitation by expanding sample sizes and testing necessity under divergent conditions.

Moreover, while NCA provides valuable insights into necessity relationships, it does not establish causality. Like other observational research methods, caution is needed when interpreting causal claims, as necessity logic differs from traditional regression-based sufficiency analyses (Dul, 2020). Future research could complement NCA with experimental or longitudinal designs to strengthen causal inferences about the role of accelerator design features in post-acceleration investment outcomes.

In addition, future research could also examine additional accelerator-level characteristics that may influence equity investment outcomes. Factors such as accelerator reputation, size, age, and experience, depth of their investor and mentor networks (Charoontham and Amornpetchkul, 2023; Dalle et al., 2023), as well as peer networking effects (Assenova and Amit, 2024; Hallen et al., 2020), are likely to

shape investor perceptions and the likelihood of high equity investments. Incorporating these dimensions could offer a more holistic understanding of the mechanisms driving post-acceleration funding success. An additional opportunity for future research would be to assess the evolution of the design elements within an accelerator program over time. Conceptually, the emerging context and the emerged context might behave differently. The older and more established accelerators are likely to be less inclined to change their program compared to new and young accelerators.

A further limitation of this study is that the available dataset does not allow for a systematic differentiation between accelerator types. While the GALI database's website provides a public list of included accelerators, the anonymization of accelerator IDs in the dataset prevents linking these entries to the programs in our sample. The majority of accelerators in the dataset appear to be private programs; however, other organizational models, such as public and university-based accelerators, are also represented. For example, the dataset includes university accelerators such as Berkeley Skydeck and LAUNCH at UC Berkeley, as well as The Rock Accelerator at Harvard Business School. Future research could address this limitation by employing datasets that allow for identification of accelerator types, thereby enabling a more fine-grained analysis of how private, public, and university accelerators may differentially shape post-acceleration outcomes.

Additionally, because this study focuses exclusively on for-profit ventures, our findings may not fully translate to non-profit or mission-driven startups. Future research could extend the scope by examining non-profit accelerators and ventures in their own right, or by introducing a comparative perspective between for-profit and non-profit setups to explore whether accelerator design and financing dynamics differ across these contexts.

Another limitation of this study is that the available data only includes national-level identifiers, without any regional or subnational information. This constraint prevents us from exploring regional variation in accelerator activity or outcomes. Future research could remedy this by integrating regional-level data, which would enable an examination of how accelerator performance may differ across innovation clusters, such as Silicon Valley or the Boston area, where local networks, institutional support, and agglomeration economies can significantly influence entrepreneurial outcomes (Stephens et al., 2019).

Lastly, we acknowledge that our sole focus is on the accelerator's side and does not specifically consider other potential factors, potentially impacting the relationship of interest (Venâncio and Jorge, 2022), e.g., factors on the entrepreneurs' side

(e.g., Chowdhury and Audretsch, 2024), ecosystems and communities (Stam and Van de Ven, 2021). We encourage future research to expand our findings, building on necessity logic.

In summary, while this study provides a novel perspective on accelerator design using necessity logic, future research should expand the scope and improve statistical robustness and theoretical implications to deepen our understanding of how accelerators influence high-growth startups' investment outcomes.

4.5.3 Conclusion

This study advances the understanding of accelerator programs by identifying the necessary conditions for securing high equity investments, particularly for high-potential startups. Our findings demonstrate that accelerators' willingness to offer grants is a broadly applicable necessary condition across multiple regions, while a structured curriculum plays a comparatively smaller necessary role (in mature accelerator ecosystems). By integrating NCA and fsQCA, we highlight how necessity logic offers critical insights into accelerator design, distinguishing between conditions required for any equity investment and those essential for securing substantial amounts. Furthermore, our results challenge the "one-size-fits-all" approach, revealing that region-specific factors, such as demo days in North America and an impact focus in South Asia, shape accelerator effectiveness. These insights provide valuable guidance for policymakers, accelerator managers, and entrepreneurs, emphasizing the need for tailored accelerator models that align with ecosystem-specific goals rather than broad, undifferentiated approaches. By doing so, this study contributes to both the theoretical and practical discourse on accelerators, equity investment, and high-growth startup development.

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Chapter 5

General conclusions

This dissertation set out to advance our understanding of high-growth potential startups, specifically academic startups and accelerated startups, and how they can be better supported in their development trajectories. While only a small fraction of new ventures ever achieve rapid scaling, high-growth startups play a disproportionate role in driving innovation, structural economic transformation, and employment growth (Acs and Mueller, 2007; Birch, 1979; Henrekson and Johansson, 2010). Given their importance, scholars and policymakers alike have increasingly sought to understand what distinguishes these firms from the vast majority of startups that grow slowly or stagnate (Barringer et al., 2005; Demir et al., 2017). This dissertation contributes to that discussion by focusing on two particularly promising, yet underexplored, categories of high-growth potential ventures: those founders emerging from academic research contexts, and those shaped by accelerator programs. These ventures are often assumed to possess superior capabilities or trajectories because of their roots in scientific innovation or structured support environments (Cohen et al., 2019b; Colombelli et al., 2016; Demir et al., 2017; Shane, 2004), yet their performance remains highly variable.

Chapters 2 and 3 form the academic entrepreneurship component of this dissertation. Chapter 2 examines how early-stage investment for academic startups can be enhanced through public support mechanisms, particularly government grants, which act as a signal of venture quality to investors. Chapter 3 complements this by examining the heterogeneity among academic founders and showing how their human capital and degrees of research-basedness shape innovation and growth outcomes. Together, these two chapters emphasize that effectively supporting academic startups requires both tailored public interventions and a deeper understanding of

the academic entrepreneurs themselves.

Chapter 4 connects back to the financing perspective of Chapter 2 but shifts focus to a different group of high-potential ventures, accelerated startups, and explores how private interventions, such as accelerator design features, influence post-program equity investment. Rather than public signals, it considers private design elements (e.g., accelerator grants, structured curricula, demo days) as necessary conditions for startups to achieve high levels of post-acceleration funding.

Across all three chapters, a unifying theme emerges: understanding and enabling high-potential startups by examining not only the enablers of growth, but also identifying the barriers and missing capabilities that can prevent high-potential startups from achieving their expected outcomes (Becker-Ritterspach et al., 2022; Demir et al., 2017). Chapters 2 and 4 share signaling theory as an underlying mechanism linking public and private support for early-stage financing, while Chapter 3 provides the conceptual basis for understanding founder-level differences that shape these outcomes. Collectively, the three studies provides a more nuanced understanding of how and when public or private interventions, such as venture capital, government support, or accelerator design, can meaningfully influence growth outcomes, particularly in environments characterized by high uncertainty, complexity, and resource scarcity (Bruderl and Schussler, 1990; Gupta et al., 2006; Lee and Lévesque, 2023; McKelvie et al., 2011; Stinchcombe, 1965). By extending these insights beyond policymakers and program designers to entrepreneurs themselves, this dissertation emphasizes that startup founders are not passive recipients of support mechanisms but active strategists who can learn to navigate and leverage these interventions to strengthen their growth trajectories. Rather than prescribing a one-size-fits-all model of support, this research highlights the importance of tailoring mechanisms to the specific challenges and growth trajectories of the ventures in question.

Together, the three studies form an integrated inquiry into the conditions under which high-growth potential can be transformed into high-growth performance, with a particular emphasis on equity financing as a critical milestone in this transition.

5.1 Chapter 2: Public Support and VC Financing

Chapter 2 contributes to a deeper understanding of how public support affects the venture capital (VC) financing trajectories of academic startups, ventures widely regarded as high-potential due to their strong scientific foundations (Bonardo et al.,

2011; Botelho et al., 2021; Shane, 2004), yet often burdened by technological complexity, market uncertainty, and doubts about entrepreneurial commitment and business acumen (Fini et al., 2023, 2022; Gubitta et al., 2016; Mathisen and Rasmussen, 2019; Meyer, 2003; Pahnke et al., 2015). Drawing on longitudinal data from the IAB/ZEW Startup Panel in Germany, the analysis shows that public support significantly increases the likelihood of receiving VC investment, and that this signaling effect is notably stronger for academic startups compared to their non-academic counterparts. The effect is especially pronounced in the high-tech manufacturing industry, where scientific validation is difficult and external certification becomes particularly valuable (Kask and Linton, 2023; Nedayvoda et al., 2021; Tech, 2018). Additionally, the signal proves strongest with business angel investors, consistent with research showing they rely more heavily on heuristic cues when evaluating startups (Berger and Hottenrott, 2021; Maxwell et al., 2011). However, the effect is short-lived, lasting only one year after public support is granted, supporting the view that signals operate as temporary certifications (Feldman and Kelley, 2003; Islam et al., 2018).

This study provides several important contributions. Theoretically, it applies signaling theory (Lerner, 1999; Spence, 1973) to identify context-specific differences in how public signals operate, particularly in academic settings where evaluating technological merit and founder commitment is more complex (e.g., Gubitta et al., 2016; Hahn et al., 2025; Hottenrott et al., 2018; Mathisen and Rasmussen, 2019; Meyer, 2003; Toole and Czarnitzki, 2007). Empirically, it provides the first comparative evidence showing that the signal of public support has a differential effect between academic and non-academic startups, addressing a gap in prior work. Practically, the findings underscore the value of incorporating signaling effects into the design and evaluation of startup support policies. Policymakers and university-linked accelerators should consider the indirect role public support plays in facilitating private investment, especially in academic ventures that may otherwise struggle to attract early equity financing. For academic founders, the findings suggest that securing public support can enhance investor appeal and should be seen as a strategic step toward attracting private capital.

In the broader context of high-growth entrepreneurship, this paper supports the core argument of the dissertation: realizing the growth potential of high-tech ventures often depends not only on their scientific promise but also on the credibility mechanisms that reduce investor uncertainty. This reinforces the importance of targeted, selective interventions that do not merely provide resources but also serve

as quality signals in capital markets, helping high-potential ventures transition from scientific promise to entrepreneurial performance.

5.2 Chapter 3: The Academic Startup Advantage

Chapter 3 contributes to a more nuanced understanding of academic entrepreneurship by unpacking the heterogeneity among academic startups and examining how different degrees of research-basedness relate to innovation and performance outcomes. Drawing on Human Capital Theory (Becker, 1964; Unger et al., 2011), we find that research-intensive academic startups tend to invest more heavily in R&D and produce more radical innovation (Marvel and Lumpkin, 2007; Stephan, 2014), but they also experience delayed commercialization and lag in early sales performance (Colombo and Piva, 2008; Gubitta et al., 2016; Mathisen and Rasmussen, 2019). In contrast, startups with lower levels of research-basedness contribute to market novelty to a lower extent, benefit from broader university human capital (Criaco et al., 2014; Nagle and Teodoridis, 2020), but do not lag in achieving market traction. Importantly, our findings challenge the common assumption that academic startups are uniformly high-potential and instead reveal divergent pathways depending on how scientific knowledge is leveraged.

This differentiation matters not only for academic research but also for the design of more tailored support mechanisms. Prior work has struggled to reconcile the inconsistent performance of academic startups, partly due to a lack of attention to the distinct contributions of general versus specific human capital. By offering an empirical typology of research-basedness, this study clarifies how innovation and commercialization outcomes are shaped by the nature of founders' academic experience. The policy implications are clear: while research-intensive ventures may require support for market access and commercialization (Colombo and Piva, 2012; Mathisen and Rasmussen, 2019; Wright et al., 2006), lower research-based academic startups may benefit more from programs that develop opportunity recognition and entrepreneurial capacity (Camuffo et al., 2020; Criaco et al., 2014; Nagle and Teodoridis, 2020). Beyond these policy implications, the findings also offer valuable insights for academic entrepreneurs themselves. Academic founders can use this typology to reflect on their strategic orientation and align their startup development accordingly. Highly research-based founders should recognize that their focus on technological or scientific challenges may lead them to overlook crucial market and managerial dimensions. Acknowledging this bias early allows them to actively seek

complementary expertise, training, or partnerships. Conversely, less research-based academic entrepreneurs may be encouraged to leverage their broader human (e.g., scientific mindset) to identify opportunities that extend beyond their direct research fields. Finally, the results highlight the importance of strategic clarity: academic ventures that remain in an ambiguous middle ground risk diluting their strengths and limiting their growth potential. By consciously identifying the type of academic venture they wish to build, academic founders can more effectively channel their capabilities toward sustainable innovation and performance.

In the broader context of this thesis, these insights strengthen the argument that high-potential entrepreneurship must be understood not only in terms of the resources startups possess, but also in terms of what may be missing or misaligned. For academic entrepreneurship to effectively contribute to innovation-led growth, we must account for the diversity of academic startup profiles and tailor interventions to the distinct growth logics they pursue. Only then can academic entrepreneurship truly fulfill its potential to drive both technological advancement and economic impact.

5.3 Chapter 4: Accelerators in Focus

Chapter 4 provides novel insights into how accelerator program design influences early-stage equity investment outcomes for high-growth startups. Building on necessity logic and drawing on NCA and fsQCA methods (Dul, 2016a,b, 2020; Ragin, 1987), we identify which program elements are not merely beneficial, but essential, without which high levels of equity investment are unlikely to occur. Most notably, we find that offering accelerator grants is a broadly applicable necessary condition for securing substantial post-acceleration BA or VC equity financing, especially in North America and, to a lesser extent, Latin America. A structured curriculum also emerges as a necessary design feature among top-performing accelerators, though its relevance is more limited. Our results also indicate that region-specific conditions matter: demo days are a necessary condition for obtaining any equity investment in North America, while an impact focus is essential for such outcomes in South Asia. These findings confirm the heterogeneity of accelerator programs and show that different contextual realities give rise to different necessary elements for startup success.

These findings advance the accelerator literature by moving beyond sufficiency-based models (e.g., Assenova and Amit, 2024; Cohen et al., 2019a) and addressing

recent calls for alternative logics and methods to unpack the heterogeneous performance of accelerator programs (Bergman and McMullen, 2022; Chan et al., 2020; Crișan et al., 2021), due to divergence in accelerator program design. From a methodological perspective, the study demonstrates how necessity-based thinking can provide new perspectives on startup support mechanisms by identifying critical bottlenecks rather than average drivers of success (Dul, 2016a,b, 2020; Dul et al., 2023; Vis and Dul, 2018). From a practical standpoint, our findings caution against the widespread replication of standard accelerator models and instead emphasize the need for context-specific program designs aligned with local entrepreneurial environments and investor expectations. For entrepreneurs, this highlights the importance of selecting accelerators whose design features align with their future investment and growth objectives.

From a broader perspective, this paper underscores the critical role accelerators can play in shaping the investment readiness and growth trajectories of early-stage startups. Much like VC itself, accelerators serve as both growth enablers and signaling mechanisms (e.g., Assenova and Amit, 2024; Cohen et al., 2019a; González-Uribe and Reyes, 2021; Vandeweghe et al., 2019). However, their capacity to fulfill these functions depends strongly on their internal design features. Without certain key elements in place, accelerators may fail to overcome the bottlenecks that limit early-stage ventures from attracting equity capital. It adds to the broader conversation in this dissertation on how targeted public or private support, be it public funding for academic startups or the internal design of accelerators, can address early-stage constraints and foster the emergence of the next generation of high-impact firms.

5.4 Broader Impact

At a societal level, this dissertation contributes to a better understanding of how high-potential startups, whether rooted in academic research or shaped through accelerator participation, can be more effectively supported to realize their economic and innovative promise. High-growth startups are often seen as engines of structural renewal, technological progress, and job creation (e.g., Acs and Mueller, 2007; Birch, 1979; Botelho et al., 2021; Colombelli et al., 2016; Henrekson and Johansson, 2010; Söderblom et al., 2015; Tartari and Stern, 2021), yet their emergence and scaling are fraught with challenges that limit the realization of their full potential (Colombo and Grilli, 2007; Colombo et al., 2010; Gbadegeshin et al., 2022; Mathisen and Rasmussen, 2019). By uncovering which support mechanisms, public

signals like government grants, private selection mechanisms like accelerator design, or human capital characteristics of academic entrepreneurs, serve as critical bottlenecks or enablers, this research provides valuable insights for policymakers, practitioners, scholars, and entrepreneurs alike. For entrepreneurs, these findings highlight how strategic engagement with public or private support mechanisms, such as aligning with signaling opportunities, leveraging structured learning environments, or demonstrating academic human capital credibility, can enhance their access to financing and long-term growth prospects.

From a scientific standpoint, the dissertation advances our conceptual and methodological understanding of early-stage financing, signaling mechanisms, and necessity logic, helping refine theories of entrepreneurial growth. Importantly, it opens new directions for future research. Promising avenues include unpacking the underlying mechanisms behind differential signaling effects, investigating which tailored interventions are most effective for different startup profiles, and exploring how necessary accelerator design elements interact with broader program structures and organizational complexities. If society is to rely on high-growth startups to tackle grand challenges and drive innovation, we must first understand how to recognize their potential and remove the barriers that keep them from scaling. This thesis takes a meaningful step in that direction.

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Appendices

A Chapter 2: Public Support and VC Financing

Table A1: Further robustness tests

	(1) FE	(2) POLS	(3) FE	(4) POLS	(5) FE	(6) POLS
Public Support	0.0738***	0.0419***	0.0753***	0.0432***	0.0657***	0.0468***
	(0.0148)	(0.0089)	(0.0148)	(0.0089)	(0.0158)	(0.0092)
Public Support x Young academic	0.2233***	0.1200***				
	(0.0632)	(0.0371)				
Young academic		-0.0137				
		(0.0131)				
Public Support x Academic at uni			0.1176*	0.0950**		
			(0.0668)	(0.0404)		
Academic still at uni				-0.0103		
				(0.0146)		
Public Support x Academic					0.1082***	0.1110***
					(0.0326)	(0.0202)
Academic						-0.0140*
						(0.0083)
Market Novelty	0.0123**	0.0337***	0.0122**	0.0337***	0.0122**	0.0383***
	(0.0048)	(0.0078)	(0.0049)	(0.0078)	(0.0048)	(0.0075)
Export	0.0266***	0.0198**	0.0256***	0.0219***	0.0182***	0.0248***
	(0.0061)	(0.0080)	(0.0060)	(0.0080)	(0.0065)	(0.0079)
1-10 full-time employees	0.0072	0.0330***	0.0052	0.0297***	0.0023	0.0444***
	(0.0058)	(0.0065)	(0.0057)	(0.0064)	(0.0058)	(0.0066)
>10 full-time employees	-0.0091	0.0332***	-0.0067	0.0329***	-0.0037	0.0235*
	(0.0103)	(0.0119)	(0.0102)	(0.0119)	(0.0114)	(0.0122)
ln Sales					0.0050***	-0.0036***
					(0.0009)	(0.0009)
Education Science		0.0015		0.0007		0.0101
		(0.0124)		(0.0124)		(0.0120)
Education Engineering		-0.0030		-0.0085		0.0087
		(0.0122)		(0.0122)		(0.0120)
Education Social Sciences		0.0426***		0.0373***		0.0490***
		(0.0117)		(0.0117)		(0.0117)
Education Humanities and Arts		-0.0075		-0.0116		-0.0076
		(0.0132)		(0.0133)		(0.0133)
Education Other fields		0.0101		0.0082		0.0105
		(0.0292)		(0.0293)		(0.0280)
Berlin		0.0446***		0.0416**		0.0432***
		(0.0162)		(0.0162)		(0.0153)
East		-0.0220**		-0.0222**		-0.0238**
		(0.0089)		(0.0089)		(0.0093)
Team		0.0266***		0.0268***		0.0282***
		(0.0075)		(0.0075)		(0.0075)
Female		-0.0094		-0.0136		-0.0043
		(0.0090)		(0.0089)		(0.0092)
Founder(s) age		-0.0002		-0.0002		0.0000
		(0.0004)		(0.0004)		(0.0004)
Number of patents before founding		-0.0004		-0.0004		-0.0003
		(0.0007)		(0.0007)		(0.0006)
Startup Experience		0.0174***		0.0190***		0.0115*
		(0.0067)		(0.0067)		(0.0068)
Industry Experience		-0.0010**		-0.0010**		-0.0010**
		(0.0004)		(0.0004)		(0.0004)
R&D activity		0.0598***		0.0588***		0.0647***
		(0.0106)		(0.0107)		(0.0099)
Opportunity Entrepreneurship		0.0022		0.0013		0.0037
		(0.0096)		(0.0097)		(0.0093)
Unemployment before startup		-0.0106		-0.0123		-0.0195*
		(0.0112)		(0.0110)		(0.0109)
Firm FE	YES	/	YES	/	YES	/
Time FE	YES	YES	YES	YES	YES	YES
Industry FE	/	YES	/	YES	/	YES
Founding year FE	/	YES	/	YES	/	YES
Observations	14737	14436	14452	14161	16440	16132
Groups (Firms)	5606	5487	5494	5378	6410	6283
R^2	0.0778	0.0980	0.0610	0.0899	0.0940	0.1241

Note: Standard errors clustered by firm. Stars indicate significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A2: The effects of subsidies on Private VC per industry

	Private VC									
	Software		High-tech manufacturing		Knowledge-intensive services		Low-tech manufacturing		Others	
	(1) FE	(2) POLS	(3) FE	(4) POLS	(5) FE	(6) POLS	(7) FE	(8) POLS	(9) FE	(10) POLS
Subsidies	0.1450***	0.0762**	0.0097	0.0561**	0.0250	0.0232**	0.0172	0.0172	-0.0070	-0.0379**
	(0.0518)	(0.0300)	(0.0280)	(0.0272)	(0.0170)	(0.0113)	(0.0309)	(0.0309)	(0.0144)	(0.0190)
Subsidies x Academic	0.0029	0.0453	0.2235***	0.0912*	0.0671*	0.0472*	0.0897	0.0897	0.1424	0.0764
	(0.0811)	(0.0510)	(0.0612)	(0.0504)	(0.0386)	(0.0244)	(0.0906)	(0.0906)	(0.1413)	(0.0668)
Academic		-0.0274		0.0374		-0.0116				0.0120
		(0.0227)		(0.0320)		(0.0100)				(0.0241)
Export	0.0258	0.0143	0.0499***	0.0133	0.0072	-0.0030	0.0729***	0.0729***	-0.0009	0.0489**
	(0.0191)	(0.0207)	(0.0163)	(0.0193)	(0.0056)	(0.0099)	(0.0219)	(0.0219)	(0.0195)	(0.0217)
Market Novelty	0.0256*	0.0721***	0.0208**	-0.0135	0.0137**	0.0403***	0.0347**	0.0347**	-0.0050	0.0351**
	(0.0143)	(0.0182)	(0.0099)	(0.0171)	(0.0056)	(0.0109)	(0.0162)	(0.0162)	(0.0095)	(0.0173)
1-10 full-time employees		0.1002***		0.0621***		0.0185***	0.0271	0.0271		0.0350**
		(0.0184)		(0.0200)		(0.0071)	(0.0217)	(0.0217)		(0.0158)
>10 full-time employees		0.1285***		0.0621*		0.0168	-0.0233	-0.0233		0.0214
		(0.0347)		(0.0322)		(0.0177)	(0.0315)	(0.0315)		(0.0219)
Firm FE	YES	/	YES	/	YES	/	YES	YES	YES	/
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	/	YES	/	YES	/	YES	/	/	/	YES
Founding year FE	/	YES	/	YES	/	YES	/	/	/	YES
Observations	2294	2259	2846	2758	7912	7763	1867	1867	2820	2768
Groups (Firms)	938	920	915	886	2734	2679	692	692	1391	1367
R^2	0.1200	0.1470	0.1517	0.1587	0.0374	0.0783	0.1070	0.1070	0.0512	0.0775

Note: The time-invariant variables for the POLS specifications are not shown in this table. Standard errors clustered by firm. Stars indicate significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table A3: Subsidies as antecedent for different VC investor types

	BA		CVC		IVC	
	(1) FE	(2) POLS	(3) FE	(4) POLS	(5) FE	(6) POLS
Subsidies	0.0319***	0.0165**	0.0110*	0.0057	0.0222**	0.0156***
	(0.0123)	(0.0082)	(0.0067)	(0.0036)	(0.0099)	(0.0055)
Subsidies x Academic	0.1152***	0.0626***	0.0555***	0.0371***	0.0763***	0.0412***
	(0.0299)	(0.0179)	(0.0198)	(0.0096)	(0.0246)	(0.0141)
Academic		-0.0055		-0.0063**		-0.0000
		(0.0080)		(0.0025)		(0.0050)
Export	0.0208***	0.0121*	0.0148***	-0.0001	0.0198***	0.0002
	(0.0057)	(0.0072)	(0.0043)	(0.0033)	(0.0044)	(0.0041)
Market Novelty	0.0198***	0.0286***	0.0083***	0.0090***	0.0095***	0.0169***
	(0.0041)	(0.0068)	(0.0026)	(0.0033)	(0.0034)	(0.0043)
1-10 full-time employees	0.0040	0.0349***	0.0039	0.0106***	0.0070*	0.0162***
	(0.0048)	(0.0058)	(0.0027)	(0.0023)	(0.0040)	(0.0033)
>10 full-time employees	-0.0210**	0.0192*	0.0015	0.0101**	0.0036	0.0281***
	(0.0088)	(0.0105)	(0.0050)	(0.0045)	(0.0081)	(0.0082)
Firm FE	YES	/	YES	/	YES	/
Time FE	YES	YES	YES	YES	YES	YES
Industry FE	/	YES	/	YES	/	YES
Founding year FE	/	YES	/	YES	/	YES
Observations	17739	17357	17739	17357	17739	17357
Groups (Firms)	6670	6524	6670	6524	6670	6524
R^2	0.0675	0.0835	0.0321	0.0417	0.0461	0.0764

Note: The time-invariant variables for the POLS specifications are not shown in this table. Standard errors clustered by firm. Stars indicate significance: * p<0.1, ** p<0.05, *** p<0.01.

Table A4: Duration of the effect of subsidies on obtaining private VC for academic startups

	Private VC					
	1 lag				2 lags	
	(1) FE	(2) POLS	(3) FE	(4) POLS	(5) FE	(6) POLS
Subsidies	-0.0107	0.0013	-0.0075	0.0016	-0.0158	0.0024
	(0.0095)	(0.0081)	(0.0093)	(0.0081)	(0.0135)	(0.0107)
Academic		-0.0027		-0.0027		-0.0034
		(0.0036)		(0.0041)		(0.0038)
Subsidies x Academic	0.0760***	0.0888***	0.0752***	0.0884***	0.1172***	0.1021***
	(0.0245)	(0.0212)	(0.0241)	(0.0212)	(0.0350)	(0.0303)
Subsidies_{t-1}	-0.0017	-0.0013	0.0004	-0.0005	0.0081	0.0045
	(0.0069)	(0.0064)	(0.0070)	(0.0064)	(0.0096)	(0.0088)
Subsidies_{t-2}					-0.0009	0.0010
					(0.0065)	(0.0061)
Subsidies_{t+1}			0.0120	0.0188		
			(0.0187)	(0.0167)		
Subsidies x Academic_{t-1}	0.0405**	0.0448***	0.0400**	0.0445***	0.0055	0.0280
	(0.0190)	(0.0168)	(0.0191)	(0.0170)	(0.0232)	(0.0207)
Subsidies x Academic_{t-2}					-0.0162	-0.0020
					(0.0164)	(0.0130)
Subsidies x Academic_{t+1}			-0.0109	-0.0166		
			(0.0304)	(0.0280)		
Market Novelty	0.0024	0.0124***	0.0057	0.0116**	0.0037	0.0091*
	(0.0061)	(0.0045)	(0.0065)	(0.0050)	(0.0069)	(0.0048)
Export	0.0050	-0.0066*	0.0120	-0.0044	0.0021	-0.0019
	(0.0067)	(0.0034)	(0.0076)	(0.0038)	(0.0076)	(0.0035)
1-10 full-time employees		0.0084***		0.0076**		0.0051*
		(0.0029)		(0.0032)		(0.0029)
>10 full-time employees		0.0152**		0.0153*		0.0200**
		(0.0071)		(0.0078)		(0.0078)
Firm FE	YES	/	YES	/	YES	/
Time FE	YES	YES	YES	YES	YES	YES
Industry FE	/	YES	/	YES	/	YES
Founding year FE	/	YES	/	YES	/	YES
Observations	13145	12858	10745	10518	9110	8900
Groups (Firms)	5235	5120	4172	4086	3747	3659
R^2	0.0231	0.0563	0.0246	0.0598	0.0357	0.0551

Note: The time-invariant variables for the POLS specifications are not shown in this table. Standard errors clustered by firm. Stars indicate significance: * p<0.1, ** p<0.05, *** p<0.01.

Table A5: Balanced summary statistics

	Unmatched				Matched			
	Academic startups N= 1531		Non-Academic startups N=5030		Academic startups N=1531		Non-Academic startups N=5030	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Time-invariant controls								
Education Science	0.433	0.246	0.193	0.156	0.433	0.246	0.428	0.245
Education Engineering	0.405	0.241	0.442	0.247	0.405	0.241	0.405	0.241
Education Social science	0.353	0.228	0.431	0.245	0.353	0.228	0.350	0.228
Education Humanities and Arts	0.089	0.081	0.086	0.079	0.089	0.081	0.088	0.081
Education Other fields	0.009	0.009	0.014	0.014	0.009	0.009	0.009	0.009
Industry=high-tech manufacturing	0.090	0.082	0.076	0.070	0.090	0.082	0.095	0.086
Industry=tech-intensive services	0.304	0.212	0.299	0.210	0.304	0.212	0.299	0.209
Industry=software	0.168	0.140	0.121	0.106	0.168	0.140	0.164	0.137
Industry=low-tech manufacturing	0.050	0.048	0.080	0.073	0.050	0.048	0.051	0.049
Industry=knowledge-intensive services	0.134	0.116	0.146	0.125	0.134	0.116	0.131	0.114
Industry=other business related services	0.036	0.034	0.062	0.058	0.036	0.034	0.035	0.034
Industry=creative consumer-related services	0.051	0.048	0.058	0.055	0.051	0.048	0.050	0.048
Industry=other consumer-related services	0.016	0.015	0.024	0.024	0.016	0.015	0.015	0.015
Industry=construction	0.010	0.010	0.038	0.037	0.010	0.010	0.010	0.010
Industry=retail	0.015	0.015	0.036	0.034	0.015	0.015	0.015	0.015
Team	0.602	0.240	0.441	0.247	0.602	0.240	0.598	0.240
Female	0.212	0.167	0.195	0.157	0.212	0.167	0.209	0.165
Founder(s) age	42.741	86.525	42.545	89.830	42.741	86.525	42.629	103.552
Number of patents before founding	0.857	64.220	0.180	2.792	0.857	64.220	1.250	60.952
Startup Experience	0.521	0.250	0.507	0.250	0.521	0.250	0.522	0.250
Industry Experience	13.845	93.996	14.436	99.340	13.845	93.996	13.867	94.572
Opportunity Entrepreneurship	0.903	0.088	0.861	0.120	0.903	0.088	0.897	0.093
Region=Berlin	0.085	0.078	0.058	0.054	0.085	0.078	0.084	0.077
Region=East	0.138	0.119	0.128	0.111	0.138	0.119	0.138	0.119
Founding year=2008	0.056	0.053	0.061	0.057	0.056	0.053	0.056	0.053
Founding year=2009	0.058	0.055	0.070	0.065	0.058	0.055	0.058	0.055
Founding year=2010	0.094	0.085	0.085	0.078	0.058	0.055	0.058	0.055
Founding year=2011	0.120	0.105	0.101	0.091	0.120	0.105	0.118	0.104
Founding year=2012	0.111	0.099	0.109	0.097	0.111	0.099	0.110	0.098
Founding year=2013	0.125	0.110	0.145	0.124	0.125	0.110	0.126	0.110
Founding year=2014	0.134	0.116	0.137	0.118	0.134	0.116	0.133	0.115
Founding year=2015	0.126	0.110	0.127	0.111	0.126	0.110	0.125	0.109
Founding year=2016	0.080	0.074	0.082	0.075	0.080	0.074	0.079	0.073
Founding year=2017	0.029	0.029	0.028	0.027	0.029	0.029	0.029	0.028
R&D Activity	0.432	0.245	0.213	0.168	0.432	0.245	0.435	0.246
Unemployment before startup	0.067	0.063	0.090	0.082	0.067	0.063	0.066	0.062

Note: Balancing for full panel dataset sample based on the time-invariant control variables with treatment "academic". For most control variables the highest moment order constraint is the first moment, the mean. For variables, *Number of patents before founding* and *Industry Experience*, the highest moment order constraint is the second moment, the variance. Maximum iterations are set at 50, and the tolerance level for convergence is set at 0.45.

Table A6: Multinomial logit on funding modes

	Funding				
	Only private VC	Private VC first	Only public support	Public support first	Private & public
Academic	0.0261	0.3929	0.2531***	1.0665***	0.7924***
	(0.1539)	(0.3014)	(0.0974)	(0.2163)	(0.2036)
Education Science	0.1965	0.5601	0.2186	0.7684***	0.6208**
	(0.2167)	(0.3946)	(0.1335)	(0.2674)	(0.2689)
Education Engineering	0.2499	0.0638	0.2454*	0.3791	0.1553
	(0.2148)	(0.3714)	(0.1328)	(0.2449)	(0.2693)
Education Social Sciences	0.8463***	0.4631	0.0147	0.6483**	0.7764***
	(0.1986)	(0.3119)	(0.1339)	(0.2517)	(0.2559)
Education Humanities and Arts	0.3574	-0.5791	0.2508	-0.5371	0.0489
	(0.2705)	(0.6522)	(0.1893)	(0.6303)	(0.4164)
Education Other fields	-0.8077	-15.5015***	0.5782	1.1967	-15.4839***
	(0.6642)	(0.5580)	(0.4482)	(0.8210)	(0.4069)
Berlin	0.5819***	1.6500***	0.2269	0.6812*	0.6761**
	(0.2169)	(0.3387)	(0.1754)	(0.3498)	(0.2896)
East	-0.0138	0.4598	1.2207***	1.3109***	0.7854***
	(0.3169)	(0.4854)	(0.1322)	(0.2607)	(0.2737)
Team	0.3323*	0.4427	0.1642	0.4668*	0.9801***
	(0.1816)	(0.3921)	(0.1061)	(0.2550)	(0.2500)
Female	-0.1957	0.1815	-0.2670**	-0.3919	-1.0190***
	(0.1992)	(0.3599)	(0.1306)	(0.2981)	(0.3283)
Founder(s) age	0.0047	0.0099	-0.0095	-0.0137	-0.0313**
	(0.0099)	(0.0161)	(0.0068)	(0.0126)	(0.0148)
Number of patents before founding	-0.0592	0.0546*	0.0715**	0.0328	-0.1776
	(0.0715)	(0.0313)	(0.0345)	(0.0404)	(0.1414)
Startup Experience	0.0323	-0.0494	-0.4298***	-0.4611**	-0.1920
	(0.1620)	(0.3400)	(0.1061)	(0.2106)	(0.2222)
Industry Experience	-0.0117	-0.0447**	-0.0019	-0.0521***	-0.0205
	(0.0110)	(0.0209)	(0.0082)	(0.0168)	(0.0163)
R&D activity	0.5519***	1.6378***	0.5103***	1.3903***	1.5459***
	(0.1599)	(0.3776)	(0.1060)	(0.2542)	(0.2507)
Opportunity Entrepreneurship	-0.0902	-0.4402	-0.4553***	2.6142***	0.3595
	(0.2733)	(0.5070)	(0.1430)	(0.7348)	(0.4640)
Unemployment before startup	-0.0660	0.9676**	1.2204***	0.9554**	0.6920*
	(0.3930)	(0.4549)	(0.1675)	(0.3847)	(0.4037)
Industry controls			YES		
Founding year controls			YES		
Observations			6536		

Note: The base category for the funding outcomes is *No funding*. Multinomial logit specification. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

B Chapter 3: The Academic Startup Advantage

Table B1: Factor loading and communalities

	Factor loadings	
Item	Research-basedness	Uniqueness
Research abilities	0.775	0.400
Research methods	0.890	0.208
Research results	0.760	0.422
Eigenvalue	1.970	

Table B2: Divergent firm and team characteristics depending on research-basedness versus non-academic

	Multinomial logit			
	Research-based quartile 1	Research-based quartile 2	Research-based quartile 3	Research-based quartile 4
Software	0.002	0.133	0.719**	0.282
	(0.268)	(0.271)	(0.306)	(0.353)
Knowledge-intensive services	0.142	0.135	0.832***	-0.076
	(0.203)	(0.224)	(0.266)	(0.325)
High-tech manufacturing	-0.167	-0.021	1.243***	0.843***
	(0.255)	(0.277)	(0.279)	(0.321)
Low-tech manufacturing	-0.446	-0.258	-0.103	-0.169
	(0.304)	(0.315)	(0.385)	(0.430)
Founding year	-0.256***	-0.213***	-0.200***	-0.193***
	(0.020)	(0.023)	(0.022)	(0.024)
Education Science	1.077***	0.938***	1.268***	1.698***
	(0.202)	(0.209)	(0.184)	(0.214)
Education Engineering	-0.037	0.294	0.548***	0.595***
	(0.199)	(0.229)	(0.181)	(0.215)
Education Social Sciences	0.271	-0.036	-0.279	-0.347
	(0.187)	(0.208)	(0.186)	(0.232)
Education Humanities and Arts	0.242	0.323	0.610**	-0.898*
	(0.247)	(0.303)	(0.252)	(0.492)
Education Other fields	0.565	-13.593***	-0.721	-0.132
	(0.479)	(0.200)	(1.048)	(1.047)
Berlin	0.284	-0.136	0.308	0.243
	(0.247)	(0.322)	(0.258)	(0.331)
East	-0.574**	-0.198	0.394**	0.518**
	(0.250)	(0.235)	(0.179)	(0.216)
Team	-0.097	-0.067	0.215	0.849***
	(0.156)	(0.170)	(0.149)	(0.202)
Female	0.256	0.100	0.196	0.194
	(0.170)	(0.190)	(0.178)	(0.217)
Founder(s) age	0.029***	0.016*	0.019**	0.011
	(0.008)	(0.009)	(0.009)	(0.010)
Number of patents before founding	0.036*	0.057***	0.012	0.062***
	(0.022)	(0.017)	(0.026)	(0.017)
Startup Experience	-0.069	0.083	-0.175	-0.698***
	(0.139)	(0.154)	(0.139)	(0.176)
Industry Experience	-0.009	-0.012	-0.021**	-0.019*
	(0.008)	(0.008)	(0.008)	(0.011)
Opportunity Entrepreneurship	0.008	-0.044	0.513**	0.977**
	(0.199)	(0.218)	(0.246)	(0.407)
Unemployment before startup	-0.328	0.133	-0.498*	-1.250**
	(0.266)	(0.252)	(0.294)	(0.506)
Observations	5873			

Note: Base category is non-academic startup. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B3: Marginal effects of multinomial logit model

	Non-academic	Research-based quartile 1	Research-based quartile 2	Research-based quartile 3	Research-based quartile 4
Software	-0.022	-0.001	0.003	0.017**	0.003
	(0.014)	(0.009)	(0.007)	(0.007)	(0.005)
Knowledge-intensive services	-0.026**	0.004	0.003	0.020***	-0.001
	(0.011)	(0.007)	(0.006)	(0.006)	(0.004)
High-tech manufacturing	-0.044***	-0.007	-0.002	0.038***	0.014***
	(0.014)	(0.008)	(0.007)	(0.009)	(0.005)
Low-tech manufacturing	0.021	-0.013	-0.005	-0.001	-0.002
	(0.013)	(0.008)	(0.007)	(0.006)	(0.005)
Founding year	0.021***	-0.008***	-0.005***	-0.005***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Education Science	-0.109***	0.034***	0.021***	0.034***	0.020***
	(0.011)	(0.007)	(0.005)	(0.005)	(0.003)
Education Engineering	-0.027**	-0.002	0.007	0.015***	0.007**
	(0.011)	(0.007)	(0.006)	(0.005)	(0.003)
Education Social Sciences	0.004	0.010	-0.001	-0.008	-0.004
	(0.010)	(0.006)	(0.005)	(0.005)	(0.003)
Education Humanities and Arts	-0.021	0.008	0.008	0.017**	-0.012*
	(0.015)	(0.008)	(0.008)	(0.007)	(0.006)
Education Other fields	0.317***	0.033**	-0.342***	-0.011	0.003
	(0.045)	(0.016)	(0.028)	(0.030)	(0.013)
Berlin	-0.019	0.011	-0.004	0.009	0.003
	(0.017)	(0.011)	(0.007)	(0.009)	(0.005)
East	-0.000	-0.016***	-0.005	0.013**	0.008**
	(0.011)	(0.005)	(0.005)	(0.007)	(0.004)
Team	-0.011	-0.004	-0.002	0.006	0.011***
	(0.008)	(0.005)	(0.004)	(0.004)	(0.002)
Female	-0.018*	0.008	0.002	0.005	0.002
	(0.010)	(0.006)	(0.005)	(0.005)	(0.003)
Founder(s) age	-0.002***	0.001***	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of patents before founding	-0.004**	0.001	0.001***	0.000	0.001***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)
Startup Experience	0.013*	-0.002	0.003	-0.005	-0.009***
	(0.008)	(0.005)	(0.004)	(0.004)	(0.002)
Industry Experience	0.001***	-0.000	-0.000	-0.001**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Opportunity Entrepreneurship	-0.024*	-0.001	-0.002	0.014**	0.012**
	(0.012)	(0.007)	(0.005)	(0.007)	(0.005)
Unemployment before startup	0.035**	-0.010	0.004	-0.014	-0.015**
	(0.015)	(0.009)	(0.006)	(0.008)	(0.007)
Observations	5873	5873	5873	5873	5873

Note: Marginals effects are related to the multinomial logit model as displayed in Table B2 . Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B4: Innovation: Logit & Probit

	R&D		Market Novelty		World Novelty	
	(1) Logit	(2) Probit	(3) Logit	(4) Probit	(5) Logit	(6) Probit
Research-based academic quartile 1	0.315*	0.190**	0.239	0.143	0.177	0.111
	(0.166)	(0.095)	(0.147)	(0.087)	(0.200)	(0.109)
Research-based academic quartile 2	0.267	0.166	0.346**	0.207**	0.243	0.141
	(0.183)	(0.105)	(0.162)	(0.097)	(0.224)	(0.120)
Research-based academic quartile 3	1.094***	0.653***	0.233	0.147	0.192	0.120
	(0.143)	(0.086)	(0.156)	(0.091)	(0.183)	(0.103)
Research-based academic quartile 4	1.535***	0.895***	0.532***	0.326***	0.669***	0.404***
	(0.208)	(0.120)	(0.192)	(0.114)	(0.207)	(0.119)
R&D			1.331***	0.811***	1.636***	0.891***
			(0.071)	(0.043)	(0.098)	(0.051)
Research: cat 1 vs cat 2	0.844	0.862	0.613	0.612	0.819	0.849
Research: cat 1 vs cat 3	0.000	0.000	0.975	0.974	0.953	0.951
Research: cat 1 vs cat 4	0.000	0.000	0.211	0.189	0.073	0.058
Research: cat 2 vs cat 3	0.000	0.000	0.602	0.641	0.853	0.890
Research: cat 2 vs cat 4	0.000	0.000	0.444	0.412	0.147	0.107
Research: cat 3 vs cat 4	0.070	0.089	0.206	0.201	0.065	0.055
Startup characteristics	YES	YES	YES	YES	YES	YES
Founding team characteristics	YES	YES	YES	YES	YES	YES
Observations	5873	5873	5873	5873	5873	5873
R^2	0.159	0.159	0.108	0.109	0.166	0.168

Note: Base category: Non-academic startups. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B5: Innovation: Human Capital & VC controls

	With HC variables			With Private VC control		
	(1) R&D	(2) Market Novelty	(3) World Novelty	(4) R&D	(5) Market Novelty	(6) World Novelty
Research-based academic quartile 1	0.049*	0.046	0.016	0.050*	0.050*	0.018
	(0.028)	(0.030)	(0.022)	(0.027)	(0.030)	(0.022)
Research-based academic quartile 2	0.044	0.064*	0.023	0.038	0.066**	0.029
	(0.031)	(0.033)	(0.025)	(0.031)	(0.033)	(0.025)
Research-based academic quartile 3	0.209***	0.049	0.030	0.195***	0.044	0.025
	(0.029)	(0.032)	(0.025)	(0.029)	(0.032)	(0.025)
Research-based academic quartile 4	0.307***	0.124***	0.121***	0.275***	0.119***	0.122***
	(0.039)	(0.040)	(0.038)	(0.039)	(0.041)	(0.039)
Industry Experience	-0.001	-0.002***	-0.000			
	(0.001)	(0.001)	(0.001)			
Startup Experience	0.049***	0.054***	0.014			
	(0.011)	(0.012)	(0.008)			
R&D		0.288***	0.203***		0.281***	0.198***
		(0.016)	(0.013)		(0.016)	(0.013)
Private VC in first 5 years				0.191***	0.115***	0.059***
				(0.020)	(0.022)	(0.018)
Research: cat 1 vs cat 2	0.906	0.678	0.825	0.757	0.702	0.744
Research: cat 1 vs cat 3	0.000	0.957	0.679	0.000	0.896	0.816
Research: cat 1 vs cat 4	0.000	0.110	0.015	0.000	0.162	0.017
Research: cat 2 vs cat 3	0.000	0.727	0.855	0.000	0.622	0.928
Research: cat 2 vs cat 4	0.000	0.236	0.030	0.000	0.308	0.041
Research: cat 3 vs cat 4	0.039	0.127	0.041	0.087	0.137	0.032
Startup characteristics	YES	YES	YES	YES	YES	YES
Founding team characteristics	YES	YES	YES	YES	YES	YES
Observations	5873	5873	5873	5851	5851	5851
R^2	0.186	0.141	0.143	0.200	0.142	0.146

Note: Base category: Non-academic startups. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B6: Innovation: Survival & Inverse probability weights

	No exit	No Insolvency	R&D		Market Novelty		World Novelty	
	(1) Probit	(2) Probit	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
Research-based academic quartile 1	-0.203**	-0.043	0.047*	0.049*	0.046	0.047	0.014	0.016
	(0.090)	(0.148)	(0.028)	(0.028)	(0.030)	(0.030)	(0.021)	(0.022)
Research-based academic quartile 2	-0.223**	-0.390***	0.047	0.050	0.067**	0.069**	0.025	0.025
	(0.099)	(0.133)	(0.031)	(0.031)	(0.033)	(0.033)	(0.025)	(0.026)
Research-based academic quartile 3	0.058	0.119	0.208***	0.208***	0.048	0.048	0.029	0.029
	(0.099)	(0.159)	(0.029)	(0.029)	(0.032)	(0.032)	(0.025)	(0.025)
Research-based academic quartile 4	-0.123	-0.130	0.300***	0.299***	0.117***	0.117***	0.119***	0.119***
	(0.120)	(0.173)	(0.039)	(0.039)	(0.040)	(0.040)	(0.038)	(0.039)
R&D	-0.053	-0.237***			0.292***	0.292***	0.206***	0.205***
	(0.047)	(0.070)			(0.016)	(0.016)	(0.013)	(0.013)
Research: cat 1 vs cat 2			0.998	0.965	0.618	0.610	0.752	0.780
Research: cat 1 vs cat 3			0.000	0.000	0.966	0.978	0.645	0.687
Research: cat 1 vs cat 4			0.000	0.000	0.146	0.150	0.015	0.018
Research: cat 2 vs cat 3			0.000	0.000	0.659	0.642	0.893	0.911
Research: cat 2 vs cat 4			0.000	0.000	0.331	0.344	0.037	0.040
Research: cat 3 vs cat 4			0.050	0.051	0.163	0.164	0.046	0.046
Startup characteristics			YES	YES	YES	YES	YES	YES
Founding team characteristics			YES	YES	YES	YES	YES	YES
Inverse probability weights			YES	YES	YES	YES	YES	YES
Observations	5873	5873	5873	5873	5873	5873	5873	5873
R^2	0.010	0.048	0.184	0.185	0.137	0.137	0.144	0.144

Note: Base category: Non-academic startups. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B7: Innovation: Alternative specification, 2-stage model approach

	R&D		Market Novelty		World Novelty	
	(1) Extensive	(2) Intensive	(3) Extensive	(4) Intensive	(5) Extensive	(6) Intensive
Academic startup	0.136***		0.064***		0.039***	
	(0.017)		(0.018)		(0.014)	
Research-basedness academic		0.033***		0.009		0.009*
		(0.006)		(0.006)		(0.005)
Software	0.308***	0.221***	0.038*	-0.119*	0.034**	-0.063
	(0.021)	(0.061)	(0.023)	(0.067)	(0.017)	(0.055)
Knowledge-intensive services	0.089***	0.063	-0.060***	-0.247***	-0.010	-0.114***
	(0.013)	(0.048)	(0.016)	(0.056)	(0.009)	(0.044)
High-tech manufacturing	0.421***	0.359***	0.059**	-0.106	0.118***	0.065
	(0.021)	(0.058)	(0.023)	(0.067)	(0.018)	(0.057)
Low-tech manufacturing	0.145***	0.146**	0.005	-0.028	0.031**	-0.022
	(0.019)	(0.073)	(0.021)	(0.082)	(0.014)	(0.067)
Founding year	0.024***	0.013*	-0.009***	-0.007	-0.004**	-0.005
	(0.002)	(0.007)	(0.002)	(0.007)	(0.002)	(0.006)
Berlin	0.051**	0.024	0.022	-0.040	0.038**	0.045
	(0.023)	(0.066)	(0.023)	(0.063)	(0.019)	(0.056)
East	-0.026	0.012	-0.024	-0.059	-0.030***	-0.022
	(0.016)	(0.045)	(0.017)	(0.046)	(0.011)	(0.039)
Education Science	0.128***	0.116***	0.075***	0.038	0.042***	0.068*
	(0.018)	(0.041)	(0.020)	(0.045)	(0.015)	(0.037)
Education Engineering	0.113***	0.152***	0.029	0.026	0.008	-0.043
	(0.017)	(0.043)	(0.019)	(0.046)	(0.014)	(0.037)
Education Social Sciences	0.059***	0.095**	0.089***	-0.000	0.030**	-0.009
	(0.016)	(0.039)	(0.018)	(0.043)	(0.013)	(0.037)
Education Humanities	0.084***	0.034	0.064***	0.034	0.018	-0.014
and Arts	(0.021)	(0.059)	(0.024)	(0.071)	(0.017)	(0.052)
Education Other fields	0.062	-0.089	0.014	0.037	0.062*	0.159
	(0.041)	(0.134)	(0.048)	(0.201)	(0.037)	(0.185)
Team	0.049***	0.017	0.016	0.069*	0.004	0.033
	(0.012)	(0.035)	(0.012)	(0.036)	(0.009)	(0.030)
Female	-0.080***	-0.128***	-0.025*	-0.100**	-0.019*	-0.083***
	(0.013)	(0.037)	(0.015)	(0.040)	(0.010)	(0.029)
Founder(s) age	-0.001	-0.004**	0.001	-0.003	0.001	0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.000)	(0.001)
Number of patents before	0.007*	-0.001	0.010***	0.010***	0.007*	0.004
founding	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)
Opportunity Entrepreneurship	0.036**	0.140***	0.055***	0.090*	0.024**	0.043
	(0.016)	(0.045)	(0.016)	(0.051)	(0.011)	(0.034)
Unemployment before startup	-0.017	-0.003	-0.016	0.013	-0.028**	-0.012
	(0.019)	(0.059)	(0.021)	(0.065)	(0.013)	(0.050)
R&D			0.293***	0.217***	0.207***	0.188***
			(0.015)	(0.038)	(0.013)	(0.032)
Observations	5873	871	5873	871	5873	871
R^2	0.176	0.214	0.136	0.144	0.141	0.160

Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B8: Innovation: Research-based as individual research constructs

	Research abilities			Research methods			Research results		
	(1) R&D	(2) Market Novelty	(3) World Novelty	(4) R&D	(5) Market Novelty	(6) World Novelty	(7) R&D	(8) Market Novelty	(9) World Novelty
Research Abilities									
Little importance	0.044	-0.002	-0.055						
	(0.043)	(0.046)	(0.034)						
High importance	0.120***	0.060	0.016						
	(0.040)	(0.044)	(0.034)						
Essential	0.181***	0.047	0.108**						
	(0.047)	(0.049)	(0.044)						
Research Methods									
Little importance				0.075*	0.027	0.025			
				(0.040)	(0.042)	(0.033)			
High importance				0.154***	0.093**	0.027			
				(0.040)	(0.044)	(0.034)			
Essential				0.174***	0.093*	0.138***			
				(0.055)	(0.056)	(0.051)			
Research Results									
Little importance							0.092**	0.013	0.004
							(0.041)	(0.042)	(0.033)
High importance							0.196***	0.077	0.060
							(0.044)	(0.048)	(0.039)
Essential							0.272***	0.160***	0.118**
							(0.049)	(0.051)	(0.047)
Startup characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Founding team characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	871	871	871	871	871	871	871	871	871
R^2	0.200	0.103	0.125	0.201	0.106	0.119	0.222	0.112	0.119

Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B9: Innovation: Interaction share of academicness

	R&D	Market Novelty	World Novelty
	(1)	(2)	(3)
Research-based academic quartile1	0.039	0.057*	0.014
	(0.031)	(0.034)	(0.024)
Research-based academic quartile 2	0.034	0.051	-0.003
	(0.038)	(0.040)	(0.028)
Research-based academic quartile 3	0.186***	0.032	0.030
	(0.038)	(0.042)	(0.032)
Research-based academic quartile 4	0.247***	0.203***	0.137**
	(0.055)	(0.058)	(0.057)
Share of academicness	0.002***	0.000	0.001*
	(0.000)	(0.000)	(0.000)
Research-based Q1 × Share of academicness	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)
Research-based Q2 × Share of academicness	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)
Research-based Q3 × Share of academicness	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)
Research-based Q4 × Share of academicness	-0.000	-0.002**	-0.001
	(0.001)	(0.001)	(0.001)
R&D		0.291***	0.203***
		(0.016)	(0.013)
Research: cat 1 vs cat 2	0.910	0.913	0.648
Research: cat 1 vs cat 3	0.002	0.639	0.673
Research: cat 1 vs cat 4	0.001	0.027	0.045
Research: cat 2 vs cat 3	0.004	0.735	0.425
Research: cat 2 vs cat 4	0.001	0.029	0.026
Research: cat 3 vs cat 4	0.356	0.015	0.097
Startup characteristics	YES	YES	YES
Founding team characteristics	YES	YES	YES
Observations	5872	5872	5872
R^2	0.187	0.137	0.144

Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B10: Sales: Fixed-effects & Accelerated Sales

	Log Sales		Accumulated Sales			
	(1) FE	(2) FE	(3) POLS	(4) POLS	(5) POLS	(6) POLS
Research-based academic quartile 1			0.070	0.122	0.160	0.208
			(0.211)	(0.211)	(0.320)	(0.321)
Research-based academic quartile 2			0.009	0.042	0.052	0.093
			(0.229)	(0.227)	(0.349)	(0.349)
Research-based academic quartile 3			-0.008	0.019	-0.195	-0.158
			(0.227)	(0.227)	(0.323)	(0.323)
Research-based academic quartile 4			-1.083***	-1.003***	-1.462***	-1.385***
			(0.364)	(0.363)	(0.440)	(0.440)
Research-based Q1 × Firm age=2	0.015	0.011			0.027	0.037
	(0.308)	(0.308)			(0.270)	(0.271)
Research-based Q1 × Firm age=3	0.373	0.384			-0.143	-0.131
	(0.346)	(0.345)			(0.311)	(0.311)
Research-based Q1 × Firm age=4	0.539	0.560			-0.213	-0.214
	(0.372)	(0.373)			(0.345)	(0.344)
Research-based Q1 × Firm age=5	0.412	0.423			-0.493	-0.518
	(0.405)	(0.404)			(0.345)	(0.347)
Research-based Q2 × Firm age=2	-0.540*	-0.560*			-0.317	-0.324
	(0.327)	(0.328)			(0.292)	(0.293)
Research-based Q2 × Firm age=3	0.083	0.076			0.043	0.025
	(0.345)	(0.346)			(0.316)	(0.318)
Research-based Q2 × Firm age=4	-0.297	-0.289			0.168	0.144
	(0.341)	(0.343)			(0.342)	(0.344)
Research-based Q2 × Firm age=5	-0.216	-0.197			0.223	0.221
	(0.447)	(0.448)			(0.360)	(0.366)
Research-based Q3 × Firm age=2	-0.110	-0.118			0.225	0.226
	(0.322)	(0.323)			(0.300)	(0.300)
Research-based Q3 × Firm age=3	0.082	0.098			0.085	0.077
	(0.341)	(0.341)			(0.340)	(0.341)
Research-based Q3 × Firm age=4	0.387	0.406			0.433	0.404
	(0.374)	(0.373)			(0.360)	(0.362)
Research-based Q3 × Firm age=5	0.671	0.677			0.588	0.535
	(0.431)	(0.430)			(0.408)	(0.406)
Research-based Q4 × Firm age=2	0.257	0.258			0.204	0.228
	(0.412)	(0.412)			(0.390)	(0.391)
Research-based Q4 × Firm age=3	0.509	0.519			0.489	0.524
	(0.466)	(0.466)			(0.502)	(0.503)
Research-based Q4 × Firm age=4	0.325	0.312			0.738	0.724
	(0.502)	(0.504)			(0.563)	(0.567)
Research-based Q4 × Firm age=5	0.914	0.858			1.541***	1.440***
	(0.557)	(0.560)			(0.542)	(0.545)
R&D			-0.708***	-0.715***	-0.710***	-0.718***
			(0.132)	(0.132)	(0.133)	(0.132)
Firm FE	YES	YES	NO	NO	NO	NO
Firm age FE	YES	YES	YES	YES	YES	YES
Industry FE	/	/	YES	YES	YES	YES
Calendar time FE	NO	YES	NO	YES	NO	YES
Other startup characteristics	/	/	YES	YES	YES	YES
Founding team characteristics	/	/	YES	YES	YES	YES
Observations	15896	15896	14318	14318	14318	14318
Groups (Firms)	5660	5660	5415	5415	5415	5415
R^2	0.266	0.268	0.241	0.243	0.241	0.244

Note: Base category: Non-academic startups. Standard errors in parentheses. Standard errors clustered by firm. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B11: Sales: Human Capital & VC controls

	Log Sales					
	Human Capital controls				VC controls	
	Without interaction		With interaction		Without	With
	(1)	(2)	(3)	(4)	(5)	(6)
Research-based academic quartile 1	0.139	0.183	0.183	0.225	0.157	0.195
	(0.188)	(0.188)	(0.318)	(0.318)	(0.188)	(0.320)
Research-based academic quartile 2	-0.022	0.007	0.089	0.131	-0.033	0.094
	(0.209)	(0.208)	(0.350)	(0.350)	(0.207)	(0.348)
Research-based academic quartile 3	0.056	0.082	-0.215	-0.180	0.032	-0.225
	(0.205)	(0.205)	(0.322)	(0.322)	(0.206)	(0.325)
Research-based academic quartile 4	-1.101***	-1.038***	-1.542***	-1.473***	-1.002***	-1.491***
	(0.324)	(0.323)	(0.434)	(0.435)	(0.320)	(0.441)
Research-based Q1 × Firm age=2			-0.136	-0.125		-0.128
			(0.305)	(0.305)		(0.306)
Research-based Q1 × Firm age=3			0.008	0.015		0.032
			(0.327)	(0.325)		(0.326)
Research-based Q1 × Firm age=4			0.033	0.037		0.060
			(0.351)	(0.351)		(0.351)
Research-based Q1 × Firm age=5			-0.119	-0.146		-0.163
			(0.370)	(0.370)		(0.374)
Research-based Q2 × Firm age=2			-0.544	-0.555*		-0.537
			(0.333)	(0.335)		(0.336)
Research-based Q2 × Firm age=3			0.033	0.007		-0.007
			(0.340)	(0.341)		(0.342)
Research-based Q2 × Firm age=4			0.033	0.005		-0.006
			(0.379)	(0.380)		(0.382)
Research-based Q2 × Firm age=5			0.122	0.111		0.089
			(0.436)	(0.439)		(0.438)
Research-based Q3 × Firm age=2			0.087	0.081		0.072
			(0.329)	(0.329)		(0.331)
Research-based Q3 × Firm age=3			0.271	0.261		0.262
			(0.339)	(0.341)		(0.342)
Research-based Q3 × Firm age=4			0.654*	0.638*		0.642*
			(0.362)	(0.362)		(0.366)
Research-based Q3 × Firm age=5			0.746*	0.710*		0.687*
			(0.408)	(0.409)		(0.415)
Research-based Q4 × Firm age=2			0.168	0.193		0.251
			(0.419)	(0.419)		(0.425)
Research-based Q4 × Firm age=3			0.680	0.701		0.782
			(0.482)	(0.482)		(0.488)
Research-based Q4 × Firm age=4			0.422	0.395		0.541
			(0.517)	(0.521)		(0.526)
Research-based Q4 × Firm age=5			1.660***	1.570***		1.583***
			(0.529)	(0.532)		(0.544)
Industry Experience	0.043***	0.043***	0.043***	0.043***		
	(0.006)	(0.006)	(0.006)	(0.006)		
Startup Experience	-0.238***	-0.235***	-0.240***	-0.237***		
	(0.089)	(0.089)	(0.089)	(0.089)		
Private VC					-0.252	-0.271
					(0.193)	(0.193)
R&D	-0.536***	-0.542***	-0.539***	-0.546***	-0.546***	-0.547***
	(0.122)	(0.122)	(0.122)	(0.122)	(0.123)	(0.123)
Firm age FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Calendar time FE	NO	YES	NO	YES	YES	YES
Other startup characteristics	YES	YES	YES	YES	YES	YES
Founding team characteristics	YES	YES	YES	YES	YES	YES
Observations	15896	15896	15896	15896	15865	15865
Groups (Firms)	5660	5660	5660	5660	5649	5649
R^2	0.177	0.180	0.178	0.181	0.172	0.173

Note: Base category: Non-academic startups. Standard errors in parentheses. Standard errors clustered by firm. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table B12: Sales: Survival & Inverse probability weights

	No exit	No insolvency	Log Sales			
			Weights exit		Weights insolvency	
	(1) Probit	(2) Probit	(3) POLS	(4) POLS	(5) POLS	(6) POLS
Research-based academic quartile 1	-0.203**	-0.043	0.163	0.208	0.165	0.212
	(0.090)	(0.148)	(0.188)	(0.321)	(0.189)	(0.321)
Research-based academic quartile 2	-0.223**	-0.390***	-0.042	0.103	-0.050	0.081
	(0.099)	(0.133)	(0.209)	(0.349)	(0.210)	(0.351)
Research-based academic quartile 3	0.058	0.119	0.019	-0.220	0.023	-0.221
	(0.099)	(0.159)	(0.207)	(0.324)	(0.208)	(0.325)
Research-based academic quartile 4	-0.123	-0.130	-1.081***	-1.521***	-1.072***	-1.498***
	(0.120)	(0.173)	(0.328)	(0.440)	(0.330)	(0.441)
Research-based Q1 × Firm age=2				-0.120		-0.134
				(0.308)		(0.306)
Research-based Q1 × Firm age=3				0.009		0.014
				(0.326)		(0.325)
Research-based Q1 × Firm age=4				0.028		0.034
				(0.353)		(0.351)
Research-based Q1 × Firm age=5				-0.162		-0.169
				(0.374)		(0.373)
Research-based Q2 × Firm age=2				-0.588*		-0.569*
				(0.339)		(0.342)
Research-based Q2 × Firm age=3				-0.026		0.003
				(0.343)		(0.347)
Research-based Q2 × Firm age=4				-0.013		-0.011
				(0.380)		(0.386)
Research-based Q2 × Firm age=5				0.082		0.108
				(0.435)		(0.437)
Research-based Q3 × Firm age=2				0.058		0.065
				(0.333)		(0.332)
Research-based Q3 × Firm age=3				0.235		0.239
				(0.343)		(0.343)
Research-based Q3 × Firm age=4				0.608*		0.618*
				(0.365)		(0.366)
Research-based Q3 × Firm age=5				0.648		0.657
				(0.413)		(0.415)
Research-based Q4 × Firm age=2				0.194		0.182
				(0.423)		(0.421)
Research-based Q4 × Firm age=3				0.674		0.661
				(0.488)		(0.489)
Research-based Q4 × Firm age=4				0.424		0.386
				(0.524)		(0.527)
Research-based Q4 × Firm age=5				1.599***		1.580***
				(0.538)		(0.536)
R&D	-0.053	-0.237***	-0.547***	-0.550***	-0.560***	-0.564***
	(0.047)	(0.070)	(0.123)	(0.123)	(0.123)	(0.123)
Firm age FE			YES	YES	YES	YES
Industry FE			YES	YES	YES	YES
Calendar time FE			YES	YES	YES	YES
Other startup characteristics			YES	YES	YES	YES
Founding team characteristics			YES	YES	YES	YES
Inverse probability weights			YES	YES	YES	YES
Observations	5873	5873	15896	15896	15896	15896
Groups (Firms)			5660	5660	5660	5660
R^2	0.010	0.048	0.172	0.173	0.172	0.173

Note: Base category: Non-academic startups. Standard errors in parentheses. Standard errors clustered by firm. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B13: Sales: Alternative specification: 2-stage approach

	Log Sales			
	(1) Extensive	(2) Intensive	(3) Extensive	(4) Intensive
Academic startup	-0.173		-0.133	
	(0.123)		(0.123)	
Research-basedness academic		-0.166***		-0.166***
		(0.043)		(0.042)
R&D	-0.583***	0.224	-0.590***	0.212
	(0.122)	(0.255)	(0.122)	(0.254)
Firm age FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Calendar time FE	NO	NO	YES	YES
Other startup characteristics	YES	YES	YES	YES
Founding team characteristics	YES	YES	YES	YES
Observations	15896	2834	15896	2834
Groups (Firms)	5660	847	5660	847
R^2	0.168	0.187	0.170	0.193

Note: Base category: Non-academic startups. Standard errors in parentheses. Standard errors clustered by firm. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B14: Sales: Research-basedness as individual research constructs

	Research abilities		Research methods		Research results	
	(1)	(2)	(3)	(4)	(5)	(6)
	Without	With	Without	With	Without	With
Little importance	-0.428	-0.957**	-0.109	-0.173	-0.049	0.375
	(0.283)	(0.485)	(0.258)	(0.436)	(0.268)	(0.416)
High importance	-0.320	-0.554	-0.351	-0.613	-0.530*	-0.965*
	(0.259)	(0.429)	(0.275)	(0.447)	(0.300)	(0.508)
Essential	-1.328***	-2.290***	-1.348***	-1.701***	-1.308***	-2.008***
	(0.353)	(0.517)	(0.422)	(0.580)	(0.379)	(0.542)
Little importance × Firm age=2		0.311		0.071		-0.497
		(0.481)		(0.426)		(0.399)
Little importance × Firm age=3		0.730		-0.048		-0.759*
		(0.476)		(0.434)		(0.426)
Little importance × Firm age=4		1.046**		0.282		-0.805*
		(0.529)		(0.469)		(0.473)
Little importance × Firm age=5		1.183**		0.152		-0.142
		(0.577)		(0.519)		(0.487)
High importance × Firm age=2		0.157		0.149		0.426
		(0.420)		(0.443)		(0.522)
High importance × Firm age=3		0.297		0.167		0.694
		(0.451)		(0.454)		(0.519)
High importance × Firm age=4		0.345		0.655		0.555
		(0.487)		(0.493)		(0.575)
High importance × Firm age=5		0.690		0.725		0.913
		(0.545)		(0.544)		(0.646)
Essential × Firm age=2		0.752		0.426		0.690
		(0.498)		(0.562)		(0.534)
Essential × Firm age=3		1.398**		0.549		0.613
		(0.550)		(0.667)		(0.596)
Essential × Firm age=4		1.359**		-0.062		1.018
		(0.602)		(0.727)		(0.636)
Essential × Firm age=5		2.295***		1.429*		1.991***
		(0.660)		(0.759)		(0.671)
R&D	0.135	0.129	0.120	0.113	0.217	0.213
	(0.250)	(0.251)	(0.253)	(0.254)	(0.251)	(0.252)
Firm age FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Calendar time FE	YES	YES	YES	YES	YES	YES
Other startup characteristics	YES	YES	YES	YES	YES	YES
Founding team characteristics	YES	YES	YES	YES	YES	YES
Observations	2834	2834	2834	2834	2834	2834
Groups (Firms)	847	847	847	847	847	847
R^2	0.194	0.198	0.192	0.194	0.193	0.197

Note: Base category: Non-academic startups. Standard errors in parentheses. Standard errors clustered by firm. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B15: Sales: Interaction share of academicness

	Log Sales	
	(1)	(2)
Research-based academic quartile 1	0.242	0.288
	(0.210)	(0.326)
Research-based academic quartile 2	-0.014	0.119
	(0.242)	(0.362)
Research-based academic quartile 3	0.144	-0.071
	(0.256)	(0.361)
Research-based academic quartile 4	-0.813*	-1.236**
	(0.427)	(0.529)
Research-based academic quartile 1 × Firm age=2		-0.133
		(0.306)
Research-based academic quartile 1 × Firm age=3		0.018
		(0.325)
Research-based academic quartile 1 × Firm age=4		0.034
		(0.351)
Research-based academic quartile 1 × Firm age=5		-0.177
		(0.374)
Research-based academic quartile 2 × Firm age=2		-0.546
		(0.336)
Research-based academic quartile 2 × Firm age=3		-0.021
		(0.341)
Research-based academic quartile 2 × Firm age=4		-0.007
		(0.383)
Research-based academic quartile 2 × Firm age=5		0.083
		(0.437)
Research-based academic quartile 3 × Firm age=2		0.030
		(0.329)
Research-based academic quartile 3 × Firm age=3		0.213
		(0.338)
Research-based academic quartile 3 × Firm age=4		0.574
		(0.363)
Research-based academic quartile 3 × Firm age=5		0.621
		(0.411)
Research-based academic quartile 4 × Firm age=2		0.203
		(0.421)
Research-based academic quartile 4 × Firm age=3		0.685
		(0.486)
Research-based academic quartile 4 × Firm age=4		0.408
		(0.523)
Research-based academic quartile 4 × Firm age=5		1.584***
		(0.541)
Share of academicness	-0.004	-0.004
	(0.003)	(0.003)
Research-based academic quartile 1 × Share of academicness	-0.001	-0.001
	(0.006)	(0.006)
Research-based academic quartile 2 × Share of academicness	0.002	0.002
	(0.006)	(0.006)
Research-based academic quartile 3 × Share of academicness	0.000	0.000
	(0.006)	(0.006)
Research-based academic quartile 4 × Share of academicness	-0.002	-0.002
	(0.008)	(0.008)
R&D	-0.537***	-0.540***
	(0.123)	(0.123)
Firm age FE	YES	YES
Industry FE	YES	YES
Calendar time FE	YES	YES
Other startup characteristics	YES	YES
Founding team characteristics	YES	YES
Observations	15892	15892
Groups (Firms)	5659	5659
R^2	0.173	0.173

Note: Base category: Non-academic startups. Standard errors in parentheses. Standard errors clustered by firm. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

C Chapter 4: Accelerators in Focus

Table C1: Robustness tests: Worldwide and equity > 0

	Worldwide				North America		Latin America		South Asia	
	Equity ≥ 0		Equity > 0		Equity > 0					
	(1)		(2)		(3)		(4)		(5)	
	d	p	d	p	d	p	d	p	d	p
Impact focus	0.250	.525	0.250	0.258	0.251	0.602	0	1	/	/
Sector focus	0.250	0.392	0.250	0.197	0.251	0.473	0	1	0.833	0.339
Program duration	0.369	0.103	0.369	0.146	0.370	0.212	0.393	0.316	0	1
Accelerator grant	0.862***	0.002	0.862***	0.000	0.865**	0.035	0.787**	0.045	0.876	0.409
Curriculum	0.783**	0.031	0.783*	0.052	0.786**	0.047	0.858	0.367	0.595	0.695
Demo days	0.132	0.803	0.132	0.832	0.132	0.915	0	1	0.714	0.625
Sample size	61		243		23		27		10	

Note: d = effect size, p = p-value. $***p < .01; **p < .05; *p < .10$

C.1 Calibrations

A first minor adaptation of the main calibration is changing the crossover point from 0.01 to 0, which leads to a change in membership scores for all the accelerators without equity investments from 0.05 to 0.5. This would reduce the range of the membership scores from 0.5 to 1. It implies that having no equity or little equity (e.g. 1000 dollars) are relatively similar (e.g. membership scores of 0.50 and 0.54) while the exceptional equity amounts with the highest membership scores will now carry more importance. A second calibration method for adapting the crossover point is to take into account the results of the NCA bottleneck analysis and use the value at which the most restrictive program feature becomes a bottleneck.[1]

[1] This would be slightly different from the value in the bottleneck table, as it would be the exact value in the bottleneck table or the observation that is right below this amount.

Table C2: Calibrations

Main sample: Accelerator level – BA and VC				
		Fully out	**Crossover**	**Fully in**
North America				
Calibration 1		0	0.01*	2,533,000 (max)
Calibration 2	Equity	0	0	2,533,000
Calibration 3		0	500,000 (bottleneck)	2,533,000
Latin America				
Calibration 1		0	0.01*	1,400,000 (max)
Calibration 2	Equity	0	0	1,400,000
Calibration 3		0	350,000 (bottleneck)	1,400,000
South Asia				
Calibration 1		0	0.01*	450,000 (max)
Calibration 2	Equity	0	0	450,000
Calibration 3		0	0.01 (bottleneck)	450,000
All				
	Duration	1 (< 3 months)	1.99* (3–6 months)	3 (> 6 months)

Note: Following Ragin (2008) and Fiss (2011), exact crossover values (0.5) are avoided. Calibration 1 uses 0.01, Calibration 2 uses 0, and Calibration 3 uses bottleneck values.

Table C3: Robustness tests: Necessary condition consistencies (fsQCA)

	Calibration 1			**Calibration 2**			**Calibration 3**		
	NA	LA	SA	NA	LA	SA	NA	LA	SA
Impact focus	0.745	0.478	**0.980**	0.604	0.406	0.883	0.740	0.442	**0.980**
Sector focus	0.685	0.392	0.811	0.577	0.369	0.750	0.727	0.422	0.811
Program duration	0.741	0.685	0.564	0.696	0.720	0.607	0.727	0.726	0.564
Accelerator grant	0.792	0.415	0.882	0.707	0.354	0.756	0.852	0.471	0.882
Curriculum	0.732	0.820	0.658	0.727	0.837	0.521	0.802	0.837	0.658
Demo days	**0.902**	0.685	0.811	**0.909**	0.692	0.855	0.891	0.669	0.811

Note: NA = North America, LA = Latin America, SA = South Asia.

Table C4: NCA analysis with calibration membership scores (BA/VC Equity)

	North America		Latin America		South Asia	
	d	p	d	p	d	p
Calibrations 1 (0, 0.01, max)						
Impact focus	0.056	0.338	0	1	1	0.138
Sector focus	0.056	0.308	0	1	0.322	0.246
Program duration	0.113	0.171	0.165	0.533	0	1
Accelerator grant	0.389**	0.018	0.322**	0.041	0.356	0.103
Curriculum	0.322*	0.082	0.378	0.475	0.178	0.494
Demo days	0.022	0.006	0	1	0.244	0.738
Calibrations 2 (0, 0, max)						
Impact focus	0.111	0.341	0	1	1	0.138
Sector focus	0.111	0.305	0	1	0.644	0.252
Program duration	0.226	0.171	0.329	0.538	0	1
Accelerator grant	0.778**	0.016	0.644**	0.036	0.771	0.109
Curriculum	0.644*	0.082	0.756	0.479	0.356	0.502
Demo days	0.044	0.914	0	1	0.489	0.743
Calibrations 3 (0, bottleneck, max)						
Impact focus	0.067	0.340	0	1	1	0.138
Sector focus	0.067	0.301	0	1	0.322	0.246
Program duration	0.147	0.180	0.221	0.544	0	1
Accelerator grant	0.500**	0.016	0.433**	0.038	0.356	0.103
Curriculum	0.422*	0.086	0.5	0.474	0.178	0.494
Demo days	0.022	0.920	0	1	0.244	0.738

Note: d = effect size, p = p-value. *** p < .01, ** p < .05, * p < .10

C.2 Selection: accelerated vs non-accelerated startups

Although it does not affect our analyses and setup of the paper, as our focus is on within-differences of accelerator programs, it could be interesting to describe the broader environment in which accelerated and non-accelerated startups are compared. Therefore, we show additional descriptive statistics regarding the worldwide sample[2] of startups that applied for an accelerated program and thus subsequently participated or not. First, we examine the selection process in the acceleration program, as accelerators tend to select the 'better' startups with higher quality (Beyhan and Fındık, 2022; Venâncio and Jorge, 2022). Table C6 (column 1) shows that there is some selection for certain startup characteristics and thus makes startups more or less likely to be accepted into an accelerator program. Additionally, we also match the accelerated and non-accelerated samples by using entropy balancing (Hainmueller, 2012) (Table C5). However, accelerators not only select higher-quality startups, but they also improve the startups and help them grow (e.g., Assenova and Amit, 2024; Cohen, 2013; Cohen et al., 2019; Hallen et al., 2020). Therefore, when controlling for the selection bias of participating in an accelerator program, the accelerated startups will perform better than non-accelerated startups (Gonzalez-Uribe and Leatherbee, 2018; González-Uribe and Reyes, 2021; Hallen et al., 2020; Venâncio and Jorge, 2022). Displayed in Table C6, accelerated startups receive higher equity amounts ($1,000) compared to non-accelerated startups, given (i) a matched sample (columns (2) and (4)) and (ii) including inverse probability weights of participating (column (3)). Additionally, the results also extend to a higher probability for accelerated startups of getting VC or BA investments (i.e., dummy variable), shown in Table C6 (column (5)).

[2]This worldwide sample does not require the presence of the accelerator design features

Table C5: Matching of firm characteristics non-accelerated vs accelerated

	Unmatched				Matched			
	Accelerated N= 1248		Non-Accelerated N=3689		Accelerated N=1248		Non-Accelerated N=3689	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Artisanal	0.028	0.027	0.028	0.028	0.028	0.027	0.028	0.027
Culture	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013
Education	0.105	0.094	0.129	0.112	0.105	0.094	0.105	0.094
Energy	0.052	0.049	0.053	0.050	0.052	0.049	0.052	0.049
Environment	0.055	0.052	0.060	0.056	0.055	0.052	0.055	0.052
Financial services	0.067	0.062	0.081	0.074	0.067	0.062	0.066	0.062
Health	0.116	0.103	0.097	0.088	0.116	0.103	0.116	0.103
Housing development	0.014	0.014	0.013	0.013	0.014	0.014	0.014	0.014
Information and communication technologies	0.091	0.083	0.076	0.071	0.091	0.083	0.091	0.083
Infrastructure/facilities development	0.010	0.010	0.013	0.013	0.010	0.010	0.010	0.010
Other	0.201	0.161	0.163	0.136	0.201	0.161	0.201	0.161
Supply chain services	0.024	0.023	0.021	0.020	0.024	0.023	0.024	0.023
Technical assistance services	0.008	0.008	0.010	0.010	0.008	0.008	0.008	0.008
Tourism	0.028	0.027	0.023	0.022	0.028	0.027	0.028	0.027
Water	0.018	0.017	0.014	0.014	0.018	0.017	0.018	0.017
Founder age	34.693	69.880	35.240	79.843	34.693	69.880	34.693	74.335
Team size	2.792	3.685	2.881	3.695	2.792	3.685	2.792	3.305
Higher education	1.504	0.265	1.492	0.262	1.504	0.265	1.504	0.262
Entrepreneurship experience	0.589	0.242	0.599	0.240	0.589	0.242	0.589	0.242
Firm age at application	1.913	3.072	1.928	3.058	1.913	3.072	1.913	2.826
Website / Social media (♯)	2.014	1.826	1.913	1.857	2.014	1.826	2.014	1.867
Number of firms applied	102.478	18493.991	151.901	24050.854	102.478	18493.991	102.904	9283.023
Operational Model: Production / Manufacturing	0.334	0.223	0.370	0.233	0.334	0.223	0.334	0.223
Operational Model: Processing / Packaging	0.177	0.146	0.192	0.155	0.177	0.146	0.177	0.146
Operational Model: Distribution	0.279	0.201	0.277	0.200	0.279	0.201	0.279	0.201
Operational Model: Wholesale / Retail	0.264	0.194	0.262	0.194	0.264	0.194	0.264	0.194
Operational Model: Services	0.628	0.234	0.621	0.235	0.628	0.234	0.628	0.234
Operational Model: Financial Services	0.103	0.093	0.115	0.102	0.103	0.093	0.103	0.093
Operational Model: Unsure	0.022	0.022	0.026	0.025	0.022	0.022	0.022	0.022
Invention-based	0.525	0.250	0.561	0.246	0.525	0.250	0.525	0.249
Patents	0.123	0.108	0.135	0.117	0.123	0.108	0.123	0.108
Log Revenue in Year$_{t-1}$	5.459	25.834	4.723	24.140	5.459	25.834	5.457	24.398
Log Number of full time employees in Year$_{t-1}$	0.798	0.889	0.823	0.838	0.798	0.889	0.798	0.787
Social motive	0.897	0.093	0.925	0.069	0.897	0.093	0.897	0.093
Copyrights	0.122	0.107	0.129	0.113	0.122	0.107	0.122	0.107
Trademarks	0.329	0.221	0.320	0.218	0.329	0.221	0.328	0.221
Application year =2014	0.043	0.041	0.041	0.039	0.043	0.041	0.043	0.041
Application year =2015	0.134	0.116	0.062	0.058	0.134	0.116	0.134	0.116
Application year =2016	0.173	0.143	0.254	0.190	0.173	0.143	0.173	0.143
Application year =2017	0.262	0.194	0.249	0.187	0.262	0.194	0.262	0.193
Application year =2018	0.199	0.159	0.238	0.181	0.199	0.159	0.199	0.159
Application year =2019	0.161	0.135	0.126	0.110	0.161	0.135	0.161	0.135

Note: Balancing based on firm characteristics with treatment, acceptance into accelerator program.

Table C6: Selection participation + Accelerated vs non-accelerated

	Participation	VC/BA Investment			
		Amount ($1,000)			Yes/No
	(1) Probit	(2) OLS	(3) OLS	(4) OLS	(5) OLS
Participated		8.365**	8.366**	7.197**	0.022***
		(4.232)	(4.175)	(3.652)	(0.008)
Artisanal	-0.016		-7.891	-6.556	-0.025**
	(0.127)		(9.894)	(4.372)	(0.013)
Culture	-0.010		-2.739	-3.040	-0.014
	(0.182)		(7.763)	(4.130)	(0.014)
Education	-0.093		9.872	7.513	0.046**
	(0.083)		(10.317)	(5.256)	(0.018)
Energy	0.066		-13.466**	-9.547***	-0.028*
	(0.100)		(6.549)	(3.404)	(0.015)
Environment	0.051		-6.780	-5.083	-0.023
	(0.096)		(10.018)	(5.661)	(0.014)
Financial services	-0.163		17.654	10.705	0.045*
	(0.123)		(16.621)	(9.476)	(0.027)
Health	0.197**		5.158	0.874	0.006
	(0.081)		(10.344)	(5.091)	(0.015)
Housing development	0.046		-6.370	-4.933	0.002
	(0.169)		(7.080)	(3.635)	(0.029)
Information and	0.185**		8.319	5.298	0.033*
communication technologies	(0.091)		(10.402)	(7.741)	(0.018)
Infrastructure/facilities development	-0.074		1.733	1.449	0.007
	(0.186)		(12.174)	(5.613)	(0.029)
Other	0.145**		-3.583	-0.894	0.011
	(0.069)		(8.206)	(3.858)	(0.013)
Supply chain services	0.117		-7.799	-7.085*	-0.005
	(0.141)		(8.273)	(3.648)	(0.018)
Technical assistance services	-0.109		-6.243	-3.644	0.045
	(0.218)		(7.397)	(3.567)	(0.050)
Tourism	0.183		0.864	6.054	0.044
	(0.136)		(8.501)	(7.084)	(0.028)
Water	0.283*		-3.946	-6.057	0.036
	(0.166)		(9.885)	(5.391)	(0.038)
Founder age	-0.006**		-0.232	-0.041	-0.001*
	(0.002)		(0.256)	(0.135)	(0.000)
Team size	-0.009		-0.324	-0.358	-0.000
	(0.010)		(0.925)	(0.503)	(0.002)
Higher education	0.053		7.864*	4.598	0.025***
	(0.041)		(4.516)	(2.809)	(0.007)
Entrepreneurship experience	-0.061		0.501	-1.655	0.020***
	(0.042)		(5.373)	(3.130)	(0.007)
Firm age at application	-0.032**		-1.125	-1.388*	-0.004
	(0.014)		(1.017)	(0.763)	(0.003)
Website / Social media (♯)	0.036**		5.136***	4.961***	0.013***
	(0.016)		(1.632)	(1.208)	(0.003)
Number of firms applied	-0.001***		0.014	-0.002	0.000
	(0.000)		(0.014)	(0.006)	(0.000)
Invention-based	-0.052		4.378	5.471**	0.016**
	(0.042)		(3.831)	(2.175)	(0.008)
Patents	-0.015		18.099**	12.880**	0.046***
	(0.062)		(8.841)	(6.015)	(0.016)
Log Revenue in Year_{t-1}	0.028***		0.369	0.174	-0.001
	(0.005)		(0.539)	(0.474)	(0.001)
Log Number of full time	-0.047*		6.101**	3.352	0.009*
employees in Year_{t-1}	(0.027)		(2.421)	(2.397)	(0.005)
Social motive	-0.185**		4.260	3.875	0.028***
	(0.072)		(3.969)	(2.772)	(0.009)
Copyrights	-0.025		-15.336***	-9.261**	-0.008
	(0.062)		(5.425)	(4.430)	(0.014)
Trademarks	0.020		11.368**	9.788***	0.009
	(0.045)		(5.475)	(3.467)	(0.009)
Application Year FE	YES	NO	YES	YES	YES
Operational Model FE	YES	NO	YES	YES	YES
Matched		YES	YES	NO	YES
Inverse probability weights		NO	NO	YES	NO
Observations	4937	4937	4937	4937	4937
R^2	0.051	0.001	0.031	0.027	0.057

Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

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