

Startup Funding Dynamics: The Role of Accelerators in Attracting Follow-on Financing

Master Thesis Project

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Summary

Startup accelerators have become key players in entrepreneurial finance, yet their effectiveness in securing follow-on funding for startups varies considerably. This thesis investigates how specific accelerator characteristics influence the funding outcomes of startups post-acceleration, focusing on three dimensions: likelihood of funding occurrence, total funding amount, and funding speed. The study utilizes a dataset of 647 startups from 18 accelerator programs within South Holland, The Netherlands. These data were collected from the Dealroom database. This research employs quantitative analysis, to test hypotheses derived from resource-based view theory.

Key findings reveal that accelerator characteristics significantly impact startup funding trajectories. Participation in non-equity accelerators increases the likelihood of securing follow-on funding, suggesting that preserving ownership and flexibility enhances investor appeal. Privately funded accelerators providing corporate access notably improve startups' chances of attracting funding due to superior networking opportunities and strategic alignments.

Further the analysis indicates that industry-specific accelerators offering corporate partnerships tend to enable startups to raise larger total funding amounts by providing deep sectoral expertise and targeted investor access. Moreover, accelerators that combine equity investment with structured training significantly boost post-program funding amounts, highlighting the critical role of comprehensive resources in enhancing startup valuation.

However, industry-specific accelerators with corporate partnerships may extend the duration required for startups to secure subsequent funding, likely due to complexities and specificity in corporate collaborations. Conversely, accelerators that focus on strategic partnerships without equity investments expedite funding timelines by reducing transaction complexities and providing robust networking channels.

This research contributes valuable insights for startups selecting accelerator programs aligned with their strategic funding objectives, accelerator managers aiming to optimize program design, and investors evaluating accelerator-backed ventures. This study is among the first that treats the accelerator characteristics synergistically and examines certain interactions of those. Extending the Resource-Based View, it demonstrates that the effectiveness of accelerator-provided resources depends not only on their presence, but on their contextual bundling, complementarity, and timely mobilization, offering a more dynamic and interaction-based perspective on startup resource acquisition. Lastly, it underscores the nuanced ways in which different accelerator characteristics collectively shape startup funding dynamics, thereby enriching the understanding of accelerator effectiveness within the entrepreneurial ecosystem.

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1. Introduction

Startups (SU) are a key driver of both innovation and economic growth, introducing disruptive technologies and business models that reshape industries. However, despite their potential, startups face significant challenges, particularly in securing the funding necessary for scale operations. The entrepreneurial ecosystem provides various financing avenues, including venture capital (VC), angel investors, corporate venture capital (CVC), crowdfunding (Ralcheva & Roosenboom, 2020), and accelerator programs (Cavallo et al., 2019; Chang, 2020; Drover et al., 2017). Each of these financing mechanisms has distinct roles in facilitating startup growth and investor engagement.

The global startup ecosystem has experienced substantial growth, supported by a diverse array of accelerator programs that aim to improve startup performance and funding prospects (Bosma et al., 2004). As accelerators continue to evolve, their role in bridging the funding gap for early-stage startups remains a topic of discussion. While some research suggests that accelerators improve access to funding by enhancing investment readiness, other studies indicate that their impact is highly dependent on program structure and industry context.

According to Dempwolf et al. (2014), there is considerable confusion among the many types of programs available for startups, especially when should choose between equity and non-equity programs. Understanding how accelerators function within this dynamic environment is critical to assessing their effectiveness in preparing startups for long-term success (Baum et al., 2004).

Despite the increasing number of accelerators, there is limited empirical evidence of their direct influence on startup funding success. While some startups successfully attract follow-on funding after completing an accelerator program, others struggle to secure investment, raising questions about the specific mechanisms that drive investor interest (Crişan et al., 2021). Moreover, accelerators operate in a rapidly changing entrepreneurial finance ecosystem where new funding sources, such as impact investors, family offices, and blockchain-based financing, are gaining prominence (Manigart & Khosravi, 2024). Much of the existing academic research has focused on evaluating the effectiveness of accelerator types—such as corporate, government-funded, equity-based, or university-affiliated models. However, recent findings suggest that this typological approach oversimplifies the complex mechanisms through which accelerators support startups (Dempwolf et al., 2014; Pauwels et al., 2016; Uhm et al., 2018; Szczukiewicz & Makowiec, 2021).

Accelerators accelerate funding success, but which accelerators do so most effectively depend on key design features and context that prior studies had not fully

disentangled (Hausberg & Korreck, 2020). This research seeks to determine the impact accelerator programs, and their corresponding characteristics have on startups ability to attract follow-on funding and identify the factors that make accelerator programs more suitable to specific startups. Moreover, it aims to investigate if different types of acceleration characteristics offer different possibilities in the funding.

The findings of this research aim to help startups select the appropriate program based on their needs, support accelerators to improve their programs, assist startups in maximizing funding opportunities, and offer insights to investors evaluating accelerator-backed ventures. Fehder & Hochberg (2014) provide empirical evidence that accelerators can enhance local VC ecosystems, but whether this effect generalizes on every local ecosystem remains an open question.

This study will focus on startups that participated in accelerators within the South-Holland ecosystem of the Netherlands. Data availability may be a limitation, particularly regarding private funding rounds. Additionally, while this study will analyze accelerator-backed start-ups' funding success, it may not fully capture the impact of all emerging investment types, such as blockchain-based financing and sovereign wealth fund investments.

All the above raise the following research question that needs to be answered to solve this research problem:

- ✓ How do specific characteristics of accelerator programs influence startups' follow-on financing outcomes?

If delving deeper and breaking down the above question into clearer and more explicit ones is essential, they would have the following form:

- Which accelerator characteristics are associated with an increased likelihood that a startup will secure follow-on funding after program completion?
- Which accelerator characteristics are associated with higher total funding amounts raised by startups post-acceleration?
- Which accelerator characteristics are associated with a shorter time to secure follow-on funding after the program?

The primary objective of this study is to investigate how specific accelerator program characteristics influence the funding trajectories of startups after acceleration. To achieve this, the research is guided by three key sub-objectives. First, building on previous findings that accelerators serve as powerful signaling mechanisms to investors (Hallen et al., 2020; Fehder & Hochberg, 2014), this study seeks to identify which specific accelerator characteristics are most strongly associated with an increased likelihood of startups securing follow-on financing. Second, the study aims to determine which accelerator characteristics are associated with higher total amounts of post-acceleration financing, reflecting how certain program designs may

be better aligned with investor expectations and the scalable growth potential of startup (Gonzalez-Uribe & Leatherbee, 2018). Lastly, the research explores which characteristics are correlated with faster access to follow-on funding, acknowledging that certain accelerator configurations may expedite startup validation and reduce time-to-investment (Bonini & Capizzi, 2019). Together, these objectives enable a multi-dimensional assessment of accelerator effectiveness, emphasizing not only whether startups receive funding, but also how much and how quickly.

Understanding the impact of accelerators on follow-on funding acquisition is crucial for startups, investors, and accelerator managers. This research aims to fill an existing gap by identifying the key success characteristics that enhance startups' funding opportunities post-accelerator, thereby contributing to the broader startup ecosystem. Furthermore, by integrating insights from recent studies, this study will offer a more comprehensive view of the evolving role of accelerators in the changing landscape of entrepreneurial finance, by examining not just whether an accelerator works, but through which characteristics. This will be done via a quantitative research approach using regression analysis models.

The importance of this research can be highlighted by the following factors. Firstly, accelerators play a key role in startup ecosystems, providing funding, mentorship, and investor access. However, not all accelerators function the same way, and their effectiveness in helping startups varies significantly. Secondly, existing research has mixed findings, some studies suggest that accelerator-backed startups perform better in fundraising (Fehder & Hochberg, 2014), while others indicate no significant impact or even negative effects (Hallen et al., 2020). This study seeks to clarify these discrepancies for the studied ecosystem.

Thirdly, while different accelerator characteristics offer distinct advantages, it remains unclear which characteristic or combination of those are most effective in increasing funding chances. Lastly, by manually gathering accelerators' characteristics using public sources and analyzing South-Holland's accelerator-backed startups using Dealroom data, this research will provide empirical evidence on whether accelerators enhance startup funding potential and which of their characteristics are most effective.

This study is primarily grounded in the Resource-Based View (RBV) of the firm, which posits that organizations achieve competitive advantage by acquiring and effectively deploying resources that can be valuable, rare, inimitable, and non-substitutable (VRIN) (Barney, 1991). Accelerators, by design, serve as institutional platforms that endow startups with such resources—ranging from human capital, social capital, to strategic partnerships and early-stage funding. RBV provides a useful framework for examining how accelerators can optimize the scope and dynamics of resource exchange between themselves and startups (Crisan et al., 2021). By empirically

examining how specific combinations of accelerator characteristics influence funding outcomes, this study demonstrates that not all accelerators provide the same resource configurations, and some bundles create greater strategic value than others. In doing so, this research aims to refine the RBV framework by identifying inter-organizational programs, such as accelerators, as critical external sources of strategic resources for early-stage firms.

Finally, to accurately assess the effectiveness of different accelerator models, there is a need for studies that compare accelerated ventures to a control group of non-accelerated ventures in order to provide robust insights into the contribution of accelerators. The absence of such a comparison in this study constitutes a limitation, while also presenting a valuable opportunity for future research within this startup ecosystem.

By addressing all the above, this study will contribute to both academic research and practical decision-making for startups, investors, and accelerator managers, helping them to better understand the true impact of accelerator programs.

2. Literature Review

2.1. Theory

The Resource-Based View (RBV) theory has been established for quite some time and has evolved significantly through ongoing research developments. RBV, originally introduced by Wernerfelt (1984) and further developed by Barney (1986, 1991), is a widely recognized theoretical framework in strategic management that seeks to explain how firms can achieve and maintain a long-term competitive advantage (Newbert, 2007; Armstrong & Shimizu, 2007). A firm's success is largely influenced by the quality and management of its resources (Sandner & Block, 2011). Barney (1991) argues that a firm's ability to gain and sustain a competitive advantage depends on its possession of key internal resources. These resources must meet four criteria to be considered strategically significant: valuable (enhance the firm's efficiency or effectiveness by supporting strategic initiatives), rare (widely possessed by competing firms, enabling uniqueness in strategy), inimitable (cannot be easily copied by competitors) and non-substitutable (cannot be replaced by other resources that offer similar strategic benefits). Resources that fulfill all four criteria contribute to sustained competitive advantage and improved firm performance. According to RBV, a firm's internal resources are the primary drivers of competitive advantage (Barney, 1986, 1991). These resources encompass all assets, skills, organizational processes, knowledge, and other elements under the company's control (Barney, 1991).

The RBV conceptualizes a firm as a bundle of resources and capabilities, which are considered the key drivers in shaping strategic decisions and achieving performance outcomes (Habbershon et al., 2003; Ravichandran et al., 2005). RBV focuses on how strategies are developed by emphasizing internal strengths over external influences like geographic location, regulatory environments, or technological fit (Wernerfelt, 1995). As a result, internally developed competencies are viewed as essential for enhancing a firm's competitive advantage.

The RBV emphasizes that a firm's strategy can be analyzed through its internal resources and capabilities, which play a crucial role in enhancing its competitive advantage. RBV is a widely adopted framework in management literature and serves as a leading paradigm in strategic management research (Barney, 1991; Peteraf, 1993; Runyan et al., 2006). The research highlights three key elements in identifying an RBV strategy: (1) Transparency - the openness and visibility of all resources involved within the company; (2) Transferability - the ability to effectively communicate and transfer knowledge across processes, particularly in production; and (3) Durability - the lasting quality of a company's products, reflecting their resilience and performance over time (Fahy, 2000; Raduan et al., 2009; Wright et al., 2001).

This theoretical framework is often used to understand organizational capacities - including how a firm mobilizes its resources - as well as its processes, structures, and systems (Barney, 1991; Zahra & Nielsen, 2002). According to RBV, organizational capabilities can be broadly categorized into functional capabilities and dynamic capabilities. Functional capabilities refer to a firm's direct or indirect ability to perform value-generating activities, such as marketing, product development, and production (Zahra & Nielsen, 2002; Pavlou & Sawy, 2006; Miles & Darroch, 2008). Dynamic capabilities involve the firm's capacity to adapt and reconfigure its internal and external competencies in response to a changing business environment (Kyläheiko et al., 2002; de Moura & Saroli, 2021). Dynamic capabilities can be further divided into two subcategories: learning abilities and social interaction skills (Teece et al., 1997).

The key to successfully implementing a resource-based strategy lies in a company's ability to effectively deploy its resources, safeguard them from imitation by competitors, and manage them efficiently. A firm's resources, capabilities, and core competencies serve as the foundation for achieving competitive advantage. Sustainable competitive advantage stems from a firm's ability to leverage and protect its unique, hard-to-replicate resources while strategically managing its internal strengths to outperform competitors (Lubis, 2022).

RBV places greater emphasis than other theoretical approaches on the importance of a firm's internal resources, both tangible (such as initial funding, facilities, technology, and financial assets) and intangible (like human capital, innovation capacity, organizational practices, management capabilities, and company culture), as key drivers in building and sustaining a competitive advantage essential for the survival of startups (Esteve-Pérez & Mañez-Castillejo 2008; Thornhill & Amit 2003).

This thesis is primarily grounded in this theoretical framework and leverages it to justify all the following.

2.2. Accelerator Programs

Accelerator programs are fixed-term, cohort-based initiatives designed to support early-stage startups by providing structured mentorship, funding, networking opportunities, and strategic guidance to enhance business growth and investment readiness. Hochberg (2016) describes accelerators as startup assistance organizations that offer education, mentorship, and funding within a limited timeframe, usually culminating in a demonstration day where ventures pitch their ideas to investors. Unlike incubators, which provide long-term support without necessarily focusing on rapid scaling, accelerators emphasize intensive, time-bound development that helps startups refine their business models, validate their markets, and connect with potential investors (Fehder & Hochberg, 2014).

Gonzalez-Uribe & Leatherbee (2018) categorize accelerator impact into two main dimensions: entrepreneurial schooling and investment signaling. Entrepreneurial schooling involves hands-on training, workshops, and mentorship to refine a startup's operations, while investment signaling ensures that the selected startups gain credibility in the eyes of venture capitalists and corporate investors. Hallen et al., (2020) further describe accelerators as mechanisms that reduce information asymmetry for investors, providing a filtering function that distinguishes high-potential startups from the broader entrepreneurial ecosystem.

The increasing role of business accelerators in startup ecosystems has drawn significant academic and practical interest. Accelerators, which offer structured mentorship, networking opportunities, and funding access, have been recognized as substantial in bridging the early-stage financing gap for startups (Hochberg, 2016). As Fowle (2017) and Szczukiewicz & Makowiec (2021) state, funding is a specialty of American and Canadian accelerators, as the European ones usually do not offer financing. As the startup landscape continues to evolve, it is crucial to assess the effectiveness of accelerators in attracting follow-on financing and fostering entrepreneurial success. Furthermore, the differences in accelerator structures, such as those that provide funding versus those that prioritize corporate partnerships, remain a key area of study (Bonini & Capizzi, 2019).

Pauwels et al., (2016, p.21) categorize the accelerator programs as follows: *“The “ecosystem builder” which is an accelerator typically set up by corporate companies that wish to develop an ecosystem of customers and stakeholders around their company...The “deal-flow maker” accelerator, which receives funding from investors such as business angels, venture capital funds or corporate venture capital and has the primary aim to identify promising investment opportunities for these investors. Lastly, the “welfare stimulator” accelerator, which typically has government agencies as a main stakeholder. The primary objective of this type of accelerator is to stimulate start-up activity and foster economic growth, either within a specific region or within a specific technological domain”.*

Corporate accelerators differ from traditional programs as they prioritize strategic alignment with corporate partners rather than purely financial outcomes. Bonini & Capizzi (2019) found that corporate accelerators enable startups to build industry-specific networks, increasing their chances of securing corporate venture capital. Additionally, research by Gonzalez-Uribe & Leatherbee (2018) supports the notion that corporate accelerators enhance long-term partnerships rather than short-term funding.

Moreover, Hallen et al. (2020) identified three key mechanisms through which accelerators contribute to startup success. First, the learning effect arises from structured mentorship and business training, which enhances decision-making

capabilities and execution speed. Second, the sorting effect ensures that only high-potential startups gain access to accelerator programs through a rigorous selection process, increasing their chances of success. Lastly, the signaling effect strengthens a startup's credibility, as participation in an accelerator serves as a positive signal to investors, making the venture more attractive for funding.

While these mechanisms provide a foundation for understanding accelerator impact, they vary significantly across different accelerator types, particularly between corporate-backed, equity-based, and government/university-sponsored accelerators (Bonini & Capizzi, 2019). Understanding these distinctions is key to assessing how accelerator participation influences follow-on financing.

RBV has been used in the field of entrepreneurship to understand and explain how emerging companies can gain a competitive edge and outperform their rivals (Alvarez & Busenitz, 2001). Radojevich-Kelley & Hoffman (2012) utilized RBV to examine the services offered by accelerators, focusing on the types of resources made available to startups to assess their post-acceleration success. Their findings emphasized that the success of startups is largely influenced by the resources provided by accelerators (Radojevich-Kelley & Hoffman, 2012). Accelerator programs play a critical role in enhancing the distinctiveness of startups by reinforcing the VRIN (Valuable, Rare, Inimitable, Non-substitutable) conditions. By offering structured access to resources, accelerators help reduce uncertainty and compensate for capability gaps commonly faced by early-stage ventures.

Strategic management of resources enhances a firm's ability to identify and capitalize on external opportunities, thereby facilitating wealth creation (Ireland et al., 2003). According to Ireland et al. (2003), the key resources essential for strategic entrepreneurship include financial capital (funding), human capital (skills, knowledge, and expertise), and social capital (the value derived from relationships with internal and external stakeholders). While Ireland et al. (2003) focused on the structural processes of acquiring, combining, and divesting resources, as well as creating unique capabilities through resource bundling and leveraging them via experienced management, Isenberg (2014) emphasized the importance of cultivating a broader entrepreneurial ecosystem to support entrepreneurship.

The design and customization of accelerator programs significantly influence the effectiveness of support provided, with tailored approaches often resulting in superior performance and greater startup uniqueness (Assenova & Amit, 2024). Specifically, accelerator programs enhance the value of startups by facilitating access to critical resources such as mentorship, market feedback, and investor networks. These elements enable startups to refine their value propositions and develop market-relevant products and services, thereby increasing their appeal to both customers and investors (Ulmer & Pape, 2022). Moreover, the temporal structure of accelerator

programs facilitates focused development within a defined timeframe, enabling startups to acquire specialized skills and align their strategies with market demands (Qin et al., 2019; Assenova & Amit, 2024). The unique combinations of resources, capabilities, and experiential learning developed within the accelerator context serve as barriers to imitation (Ulmer & Pape, 2022). Additionally, accelerators support the development of non-substitutable products and services by guiding startups in addressing complex societal and market challenges.

Accelerator programs play a crucial role in addressing major challenges faced by startups, such as lack of funding (Fehder & Hochberg, 2018), limited market understanding, inadequate marketing knowledge, difficulty in reaching customers, and insufficient business experience (Radojevich-Kelley & Hoffman, 2012).

Research suggests that accelerator-backed startups experience faster growth, better investment outcomes, and improved operational performance compared to non-accelerated startups (Stayton & Mangematin, 2019). Hochberg (2016) found that accelerators increase regional venture capital investment by 104%, while Fehder & Hochberg (2014) demonstrated that they attract new investors to emerging startup hubs. Winston Smith et al. (2013) found that startups participating in accelerator programs secure their first round of follow-up funding significantly earlier than those that do not, highlighting the value accelerators provide in overcoming early-stage obstacles. Uhm et al. (2018) found that accelerators play an active role in the venture creation process by assisting startups in securing vital resources, refining their business models, and formulating effective market entry strategies. They emphasize that key resources and capabilities, such as human capital, facility support, global networks, financial investment, and strategic connections, are critical to startup success and must be carefully considered during the planning and development of the new venture.

However, not all accelerators function in the same way. Some programs focus on mentorship and industry connections, whereas others provide direct funding (Gonzalez-Uribe & Leatherbee, 2018). The RBV further suggests that these various organizational practices and capabilities interact synergistically to create a competitive advantage (Malhotra et al., 2025). Within this framework, funding, mentorship, social capital, and human capital are considered strategic resources that can drive superior performance. Research also shows inconsistent results regarding the effectiveness of accelerators. Some programs lead to higher funding success, while others show no impact or even negative outcomes due to ineffective program structure or misaligned incentives (Hallen et al., 2020). This raises the question of when and how accelerators contribute positively to subsequent financing.

2.3. Start-Up Success Measurement

Evaluating the performance of startups following their participation in accelerator programs is a complex challenge, particularly given the heterogeneity of ventures, sectors, and growth trajectories (Prohorovs et al., 2018; Rompho, 2018; Santisteban et al., 2021). Traditional approaches often reduce success to binary outcomes, but recent scholarship and practical observations emphasize the importance of granular, multidimensional performance indicators (Drori & Wright, 2018; Uhm et al., 2018). In alignment with this perspective, the present study adopts three distinct but interconnected metrics of startup success: (1) funding occurrence, (2) funding amount, and (3) funding speed.

Success Measurement	Description
Funding Occurrence	A binary indicator of whether a startup secures any follow-on funding after the accelerator participation.
Funding Amount	The total monetary value of funding secured by the startup after the accelerator participation.
Funding Speed	The time interval from accelerator graduation to the next funding round.

Table 1

The occurrence of follow-on funding - whether a startup raises money after participating in an accelerator - is the most direct and widely accepted indicator of investment success (Hallen et al., 2020; Hochberg, 2016). Numerous studies support the idea that accelerator involvement enhances investor trust, thus increasing the likelihood of funding. For instance, Gonzalez-Uribe and Leatherbee (2018) demonstrate that startups in structured acceleration programs are more likely to raise capital compared to their non-accelerated counterparts, emphasizing the causal relationship between program participation and follow-on financing.

In the context of start-ups, RBV-driven research frequently points to financial capital as a crucial determinant of survival (Cooper et al., 1994; Coleman et al., 2013). Financial capital, as a tangible resource, enables new ventures to develop unique capabilities and gain a lasting competitive edge (Yang et al., 2017). It is particularly vital in highly innovative sectors, where access to funding can free firms from financial constraints and improve their survival prospects (Bates, 1990; Cooper et al., 1994; Coleman et al., 2013). Some scholars argue that firms with greater initial capital can sustain operations longer and secure additional funding before exhausting their resources (Cooper et al., 1994; Camilleri & Bresciani, 2022). Others suggest that entrepreneurs with access to funding are less likely to experience business failure (Coleman et al., 2013). Therefore, financial capital is viewed as a key internal resource that supports the development of non-replicable capabilities and underpins competitive advantage (Barney, 1991; Yang et al., 2017).

Accelerators can be understood as resource providers that enrich participating startups' resource endowments. For example, Uhm et al., (2018, p.258) document that startup accelerators provide the “*various types of assets, systems, knowledge and information*” needed to achieve entrepreneurial goals, while also improving founders' skills. In their cross-country case studies, they note that accelerators enhance early-stage firms' access to resources and investors, which highly affects the success rates of early-stage start-ups. A funding round also sends a positive signal of venture quality and credibility (as funding events act as valuable signals to external) (Camilleri & Bresciani, 2022; Drori & Wright, 2018; Mayya & Huang, 2025). Empirical studies show that equity-backed or privately funded accelerators often provide more credible signals because they indicate skin-in-the-game and market validation (Pauwels et al., 2016; Drori & Wright, 2018).

Furthermore, the resources of accelerators' mentor and investor networks help facilitate funding occurrences by sharing information and reducing information asymmetries. In other words, the accelerator functions as a “*dealmaker*” that builds social capital and connects start-ups to investors (Hochberg, 2016, p. 33). A function that is also observed by Dalle et al., (2025).

Therefore, funding occurrence is not merely a binary success flag but a critical point for growth. Its relevance is magnified in the context of early-stage startups, which typically lack sufficient internal resources and depend heavily on external financing for survival and scaling (Davila et al., 2003).

While funding occurrence denotes the presence of investor interest, it does not capture its magnitude. Hence, the total amount of funding received post-acceleration becomes a crucial complementary metric. Higher funding volumes typically indicate greater investor confidence, stronger business models, and higher valuation projections (Assenova & Amit, 2024). Assenova & Amit (2024) also demonstrate that equity-backed accelerators are particularly effective at helping startups raise substantial follow-on rounds, underscoring that accelerator characteristics influence not only the likelihood of funding, but also its magnitude.

From the Resource-Based View (Hsu, 2007; Camilleri & Bresciani, 2022; Barney, 1991), larger capital inflows enable startups to access and deploy valuable resources that enhance competitive advantage and performance. Empirical evidence supports this claim, as Hochberg (2016) and Pauwels et al. (2016) find that accelerators associated with higher post-program funding amounts tend to be those with more intensive investor networks and financial support services. Moreover, startups participating in industry-specific accelerators gain domain expertise and targeted investor access, which enhances their ability to attract larger funding rounds (Cohen et al., 2019).

Larger funding amounts indicate stronger market endorsement and investors' willingness to invest more money signals higher perceived quality or lower perceived

risk (Davila et al., 2003). Furthermore, start-ups embedded in richer networks can attract larger investments (Dalle et al., 2025). This helps explain why startups from accelerators with rich network integration tend to perform better in securing both the amount and speed of funding (Stayton & Mangematin, 2019; Hochberg, 2016). Therefore, funding amount captures both the enhanced resource base and the amplified quality resulting from acceleration (Davila et al., 2003; Uhm et al., 2018; Gonzalez-Uribe & Leatherbee, 2018).

The third measurement is the speed at which a startup secures investment after completing an accelerator program, which is increasingly recognized as an important dimension of venture success. This indicator reflects both startup readiness and the responsiveness of the investment ecosystem (Carniel & Dalle, 2020; Stayton & Mangematin, 2019; Cumming & Zhang, 2019). Faster funding suggests that startups are better prepared and that accelerators have effectively connected them to timely and relevant investor networks.

Obtaining funding quickly means strong initial momentum and quality, startups prove their viability in a shorter period. Moreover, quick funding validates the accelerator's role in accelerating the startup lifecycle. This aligns with Drori and Wright's (2018, p. 12) characterization of accelerators as "*agents of change*" that compress the timeline for venture growth. Moreover, slow funding may show investor hesitance, poor market alignment, or weak accelerator support, thus providing additional diagnostic value (Drori & Wright, 2018; Uhm et al., 2018). From an RBV angle (Barney, 1991), shorter time to funding means the firm secures crucial resources earlier, accelerating its resource accumulation. Based on literature traits like training and corporate partnerships can be seen as mechanisms to bundle complementary resources, accelerating the venture's readiness for investment and growth (Gonzalez-Uribe & Leatherbee, 2018). Additionally, developing more investor ties during acceleration correlates with improved survival rates and faster capital raising success (Mejia & Gopal, 2015).

All these predict that by building entrepreneurs' networks and trust, accelerators enhance startups' ability to mobilize funding (Nahapiet & Ghoshal, 1998; Dalle et al., 2025; Shane & Cable, 2002). Thus, funding speed is a performance metric that captures an accelerator's efficiency within a shorter time frame (Hallen et al., 2020; Uhm et al., 2018) and the time-sensitive value of early resource access in the venture's emergent path.

Taken together, these three metrics provide a comprehensive measure of startup performance in relation to securing external funding.

2.4. Hypothesis Development

Building on the theory, accelerator literature, and startup performance measurements literature, this section develops hypotheses on how specific accelerator characteristics influence startup funding outcomes. Prior research shows that accelerators vary in design and focus, which can lead to different venture performance trajectories (Drori & Wright, 2018; Pauwels et al., 2016). These programs have grown in diverse forms (Dempwolf et al., 2014; Drori & Wright, 2018). Given these differences, entrepreneurs view accelerator participation as a strategic means to enhance their visibility and improve their chances of securing investment (Pauwels et al., 2016). However, the extent of this benefit likely depends on which resources and features an accelerator provides (Cohen et al., 2019). Each set of hypotheses highlights theoretically influential accelerator characteristics (binary features). In line with literature insights (Pauwels et al., 2016; Hallen et al., 2020), repetition of characteristics across outcomes is avoided.

2.4.1. Funding Occurrence

The likelihood of follow-on funding raised by accelerator-backed startups is expected to vary depending on the specific characteristics of the accelerator program. Prior research has found that participation in accelerators increases the likelihood of startups receiving follow-on funding (Hallen et al., 2020; Gonzalez-Uribe & Leatherbee, 2018). While much of this literature has focused on equity-based programs, government-backed non-equity programs such as Start-Up Chile (Gonzalez-Uribe & Leatherbee, 2018) have shown that, even in the absence of financial investment, structured support and exposure can enhance a startup's appeal to investors. Accelerator participation alone certifies startup quality, thereby reducing investor uncertainty (Drori & Wright, 2018).

In recent years, a discernible shift has emerged from equity-based to non-equity accelerator models, particularly among corporate, government-backed, and university-affiliated programs. This transformation is driven by a combination of founder preferences for retaining ownership and the strategic interests of accelerators that aim to foster innovation without equity entanglements (Hochberg, 2016; Dempwolf et al., 2014). Non-equity models lower the entry barrier for startups and allow accelerators to support a broader and more diverse set of ventures (Pauwels et al., 2016). Moreover, the availability of public grants and sector-specific development funds in Europe has contributed to the rise of non-equity funding structures, aligning accelerator missions more closely with broader policy objectives rather than direct financial returns (Fehder & Hochberg, 2014). As such, this shift reflects an evolving accelerator landscape in which value creation is increasingly decoupled from equity ownership.

From the above, it is evident that fewer studies have examined this characteristic; however, as more accelerator programs shift toward or evolve into non-equity models, it becomes increasingly important to address this gap in literature.

From a Resource-Based View, non-equity accelerators provide startups with valuable resources, typically offering mentorship, structured learning and access to networks without diluting founder ownership. Accelerated ventures thus accumulate capabilities and social ties that prospective investors value. Because non-equity funding programs impose no dilution, founders may retain more control and motivation, potentially increasing their commitment.

From an economic standpoint, non-equity accelerators reduce dilution concerns, preserve founder control, and simplify the cap table, thereby making the startup more attractive to subsequent investors. Unlike equity-based accelerators, which may impose early valuation constraints or signal risk through dilution, non-equity programs allow founders to approach future funding negotiations with full ownership and greater flexibility in terms. Moreover, they help reduce principal-agent concerns by avoiding conflicting claims from early investors.

The logic follows that participation in a structured, non-equity accelerator not only signals capability and commitment but also avoids early financial entanglements, thereby increasing the likelihood of attracting post-program investment. Logic and related evidence imply that participating in any reputable accelerator (including non-equity) should enhance post-program funding likelihood.

Thus, it is expected that non-equity accelerators enhance the likelihood of funding occurrence. This hypothesis fills a gap, as empirical work has rarely isolated the non-equity model's effect on funding. Formally:

Hypothesis 1a: Participation in a non-equity funding accelerator positively influences the likelihood of a startup securing post-program funding.

Accelerators differ not only in terms of their funding models but also in their ownership structures and sponsor types. Privately funded accelerator programs often demonstrate greater market orientation and flexibility compared to government programs (Cohen et al., 2019). A privately funded accelerator is typically backed by venture investors or entrepreneurs, offering startups direct access to private capital markets and the venture community. This institutional affiliation signals that participating startups have undergone rigorous selection processes and are well-positioned for growth, thereby increasing their likelihood of securing follow-on funding.

However, among private accelerators, those that offer startups access to corporate partners may facilitate superior strategic and financial outcomes. Access to corporate partners exposes startups to high-value networks, industry-specific feedback, and early pilot opportunities, aligning with the Resource-Based View (Hochberg, 2016; Seitz et al., 2024). In practice, specialized corporate accelerators have been shown to create “win–win” relationships, whereby corporations gain insight and access to innovation, while startups benefit from “smart financing” and strategic networks, factors that can significantly enhance their fundraising prospects (Seitz et al., 2024).

Under the Resource-Based View (RBV), corporate-affiliated accelerators provide startups with valuable, rare, and hard-to-replicate assets (Collis and Montgomery 1995). From RBV perspective, these ties constitute strategic assets, as corporate partners provide startups valuable inputs such as industry expertise, customer pipelines, specialized equipment and may also offer smart financing or follow-on investment (Canovas-Saiz et al. 2020). Private funders similarly bring venture funding, market knowledge, and legitimacy. Consequently, the combination of private funding and corporate access equips startups with a diverse and complementary bundle of resources and networks, assets that are often unavailable in other types of programs.

Empirical evidence supports these conceptual arguments. On the private-funding side, research has shown that investor-sponsored accelerators outperform public or non-profit programs in terms of startup funding outcomes. For example, Seitz et al. (2024) note that accelerators backed by venture investors tend to facilitate greater venture capital acquisition for their portfolio firms compared to corporate- or government-sponsored programs. Simultaneously, corporate involvement also demonstrates a positive track record. Cohen et al. (2019) report that corporate accelerators enhance startups’ ability to secure capital.

Despite its intuitive appeal, this intersection remains surprisingly understudied in the existing literature. Most accelerator research has examined funding models and corporate involvement as distinct dimensions, rather than exploring their joint or interactive effects. Reviews note that we still have “*little understanding of how different forms of accelerators operate, and what outcomes they produce across different contexts*” (Crişan et al., 2021, p. 62). Similarly, Seitz et al. (2024) observe that while corporate accelerators are proliferating, their effects on startup funding remain ambiguous. To this study’s knowledge, no prior research has explicitly compared startups in privately funded accelerators with and without structured corporate partnerships. Thus, there is a conceptual gap in understanding the marginal effect of corporate access within privately-run accelerators, which this hypothesis aims to address. Formally:

Hypothesis 1b: Startups participating in private funded programs that provide access to corporate partners are associated with a higher likelihood of securing funding.

2.4.2. Funding Amount

The total amount of follow-on funding raised by accelerator-backed startups is also expected to vary based on accelerator characteristics. This thesis suggests that certain program's features enable ventures to attract significantly greater post-acceleration capital.

Conversely, accelerator design features that are overly niche or too closely aligned with a sponsoring corporation may reduce funding amount. Prior studies highlight that a focused program can create value by aligning startups with mentors, corporate partners, and investors who possess deep understanding of the industry's nuances and capital needs (Drori & Wright, 2018; Pauwels et al., 2016). By operating within a specialized niche, accelerators may also attract investors who are more inclined to make substantial investments within that domain (Gonzalez-Uribe & Leatherbee, 2018; Bliemel et al., 2018). Further empirical evidence suggests that startups graduating from industry-focused accelerators tend to secure funding if the industry itself is capital-intensive or has robust investor interest. Industry-specific accelerators offer targeted mentorship and sector-aligned investor access, which are especially valuable in capital-intensive fields (Drori & Wright, 2018; Pauwels et al., 2016).

These accelerators act as resource integrators, enabling startups to build specialized knowledge, acquire regulatory or technical insights and establish connections with partners or investors, who are particularly active in the targeted domain. Startups graduating from such programs are often more 'investor-ready' in sector-specific terms, which enhances investor confidence and increases the likelihood of securing larger investment rounds.

Nonetheless, most existing studies highlight this point descriptively, without providing robust comparative data on the actual amounts of capital raised by startups. While Gonzalez-Uribe and Leatherbee (2018) underscore the importance of accelerator program design, empirical research that isolates the impact of sectoral specialization on total funding remains limited.

Likewise, corporate accelerator studies indicate that programs selecting ventures closely aligned with the parent company's industry tend to drive higher startup growth (Seitz et al., 2024)—a pattern likely driven by strong funding support from strategically aligned investors. Further theoretical reasoning supports this view. From a Resource-Based View (RBV) perspective, industry-specific accelerators concentrate valuable tangible and intangible resources, such as deep domain knowledge, tailored mentorship and sector-relevant networks, that enhance the attractiveness of participating startups. In addition, accelerators function as platforms that connect ventures with potential investors. By focusing on a specific industry, specialized programs can improve the quality of investor - startup matching, thereby increasing the likelihood and scale of follow-on funding (Dalle et al., 2025).

When these two characteristics are paired together, startups benefit from deeper sectoral knowledge and high-quality industry linkages, which are economically valuable in high-capital sectors. These dynamics are consistent with Resource-Based View, which emphasizes the strategic value of aligning with domain-specific resources.

Few prior works have explicitly tested the joint effect, by analyzing both dimensions simultaneously, thus this study aims to address that gap. From an economic perspective, the combination of specialization and corporate backing reduces search costs and increases the efficiency of capital deployment. Investors operating within niche sectors gain greater confidence when startups are vetted by both experts and corporates within that field. This targeted environment increases the likelihood of larger funding rounds, as it reflects a smaller pool of better-informed capital with greater willingness to invest deeply in sector-aligned ventures. Formally:

Hypothesis 2a: Startups participating in industry specific accelerators that provide corporate access will secure higher total funding amounts.

Programs also differ in whether they offer equity-based funding, and this choice interacts with other services provided. A notable empirical finding is that providing capital alone is often insufficient. It's the combination of funding and training that tends to generate more favorable outcomes. In a randomized study of Start-Up Chile program, all startups received a stipend (non-equity grant) plus co-working space, while only a selected subset received additional entrepreneurship training (Gonzalez-Uribe & Leatherbee, 2018). The results showed that the "basic services" of funding and space alone did not significantly enhance startup performance. However, when training was bundled with funding, the effect was substantial. Ventures that received both were 21% more likely to secure follow-on financing compared to those that received funding alone (Gonzalez-Uribe & Leatherbee, 2018).

These findings demonstrate a clear interaction effect, indicating that seed funding alone is insufficient to drive follow-on investment unless it is coupled with mentorship and entrepreneurial education. From a Resource-Based View (RBV) perspective, this underscores the idea that financial capital must be complemented by valuable, rare, and inimitable resources such as human capital (skills and knowledge) and social capital (networks and guidance) to generate a sustainable competitive advantage. Notably, while the study identified a significant increase in the likelihood of securing subsequent funding, it did not assess the magnitude of the capital raised.

Providing startups with initial capital in the form of equity funding alongside intensive training can produce a synergistic effect on subsequent fundraising outcomes. The Resource-Based View suggests that direct funding plus skill-building offers complementary resources. The capital injection alleviates early financial constraints,

while trainings (mentorship, curricula, and workshops) build human and social capital. In practice, this means ventures emerge from the program with both enhanced resources and more refined business plans. Assenova and Amit (2024) find that accelerators with structured educational curricula (training) do not necessarily increase the probability of funding, but their participants raise about \$4.85 million more on average. Extending this, if the accelerator also provides equity investment, it likely amplifies the amount of capital raised.

From an economic lens, this combination creates synergy. Equity investment supplies working capital, while training enhances managerial effectiveness - both factors that improve startup valuation and attract investor interest.

Although these mechanisms are individually well-established, few studies explicitly test the interaction between funding and training on total funding outcomes. Most assessments isolate either investment or education. Therefore, this hypothesis contributes to addressing a gap in understanding how accelerator design affects post-program funding performance through integrated support mechanisms. Formally:

Hypothesis 2b: Startups that participate in accelerator programs that offer equity funding along with training will secure higher total amount of funding.

2.4.3. Funding Speed

The speed at which accelerator graduates secure their first post-program funding (measured in months from completion) is another interesting performance metric. Accelerator programs are typically designed to shorten the time it takes for startups to secure follow-on funding by providing mentorship, investor connections, and early validation (Hallen et al., 2014; Pauwels et al., 2016; Winston Smith et al., 2013). It is well established in the literature (Cohen et al., 2019; Hallen et al., 2020) that accelerator characteristics related to mentoring intensity, market focus and program goals influence the time it takes for startups to obtain financing. Accelerators that emphasize education and mentorship are more likely to accelerate the funding timeline by making startups more “investor-ready” upon graduation. However, there remain certain characteristics and intersections that have yet to be systematically studied. Moreover, research suggests that the nature and combination of specific accelerator characteristics can lead to divergent funding timelines.

While industry-specific accelerators with corporate access can enhance the total capital eventually raised, they may also delay the process of securing that capital. Relationship-specific investments between startups and corporate sponsors can lead other investors to perceive the venture as locked into a narrow trajectory. Economic reasoning on hold-up problems suggests that excessive specificity in strategic

relationships can reduce flexibility, prolong negotiations and increase transaction complexity (Williamson, 1985).

Empirical work supports this logic. Corporate-aligned accelerators often require startups to adhere to corporate validation procedures, including pilot testing or integration processes, which can extend the timeline before external funding is sought or secured (Seitz et al., 2024). Cheng et al. (2023) further suggest that while specialization may accelerate time-to-market, it can simultaneously delay broader fundraising efforts, as startups concentrate on meeting the demands of corporate pilots rather than pursuing scalable growth.

Under the Resource-Based View (RBV), while these resources are highly valuable in the long term, their specificity can introduce short-term frictions in the funding process. Specifically, when a startup develops resource-dependent relationships with corporates, it becomes embedded in relationship-specific assets that are not easily transferable or universally valuable to other investors. As a result, these highly specific, high-value assets may take longer to materialize into external funding—particularly when they are tied to strategic partnerships. Consequently, the time to funding may be prolonged, even though the long-term funding ceiling is potentially higher.

As a result, accelerators that are both industry-specific and corporate-linked may inadvertently extend the time required to secure funding. This hypothesis contributes to resolving ambiguity in the existing literature by treating time-to-funding as a distinct outcome and testing whether the intensive support associated with corporate specialization comes at the expense of funding speed. Formally:

Hypothesis 3a: Startups participating in industry-specific accelerator programs that provide corporate access will receive follow-on funding with a delay.

On the other hand, strategic partnerships without equity involvement can accelerate funding by minimizing early-stage bargaining complexity. Intuitively, without an equity share to negotiate, deals can close more quickly, while the partnership itself still provides valuable networks and support. Unlike equity-taking accelerators, non-equity strategic partners do not impose ownership claims, thereby reducing legal and coordination hurdles in follow-on investments. This added flexibility can expedite negotiations. A non-dilutive accelerator endorsement may serve as a strong positive signal to investors, reducing perceived uncertainty and shortening time-to-close (Seitz et al., 2024). Similarly, strategic partners can offer legitimacy and access to networks that rapidly open doors to external capital.

Assenova and Amit (2024) suggest that when an accelerator forgoes direct investment, acting as a strong strategic partner can still enhance startup outcomes by opening alternative funding channels or revenue opportunities. Empirically, when an

accelerator's design excludes equity investment, its value hinges on the strength of the networks it provides. A non-equity program with robust corporate or investor partnerships can still drive significant fundraising success, whereas non-equity programs lacking such connections tend to underperform in terms of funding outcomes (Ortega & Harrison, 2025).

Economically, removing the accelerator's equity claim reduces agency and coordination costs, thereby enabling faster access to outside investment. The underlying logic is that strategic partnerships generate "tangible wins" for both parties, and with no equity stake to negotiate, startups are better positioned to raise external funding quickly once those wins materialize.

From the perspective of the Resource-Based View (RBV), when a non-equity accelerator acts as a strategic partner, it embeds RBV-aligned resources, such as access to critical networks, industry credibility, technical expertise, and market validation, into the startup's ecosystem without imposing ownership constraints. This theoretical lens suggests that the startup can rapidly signal access to valuable, hard-to-imitate resources without being encumbered by equity entanglements, thereby accelerating its path toward external investment.

Although there is a growing tendency toward this type of collaboration, no research has explicitly examined whether the combination of non-equity acceleration and strategic partnership leads to faster funding. This hypothesis addresses that gap by predicting that startups from such programs secure financing more quickly on average than those from alternative models. Theoretically, this aligns with platform dynamics, where dominant accelerators can accelerate outcomes, and with resource-based arguments suggesting that reduced transaction complexity (due to the absence of an equity sale) facilitates a faster funding process. Formally:

Hypothesis 3b: Startups that participate accelerators that do not take equity while acting as a strategic partner will obtain funding faster.

Each of the above hypothesis connects specific accelerator characteristics and targets underexamined interactions in relation to funding outcomes, drawing on both theoretical frameworks and empirical insights. By framing the research within the Resource-Based View (RBV) theory, this study posits that accelerator programs may satisfy the VRIN (Valuable, Rare, Inimitable, Non-substitutable) criteria (Barney, 1991). Specifically, the research investigates whether participation in accelerator programs endows startups with unique capabilities that enhance their value proposition and improve their chances of securing external funding.

2.5. Conceptual Framework

Before proceeding, it is useful to present a conceptual framework that synthesizes the key elements discussed thus far. This framework provides a visual overview of the accelerator characteristics examined in this study and illustrates how they relate to the three funding-related outcomes.

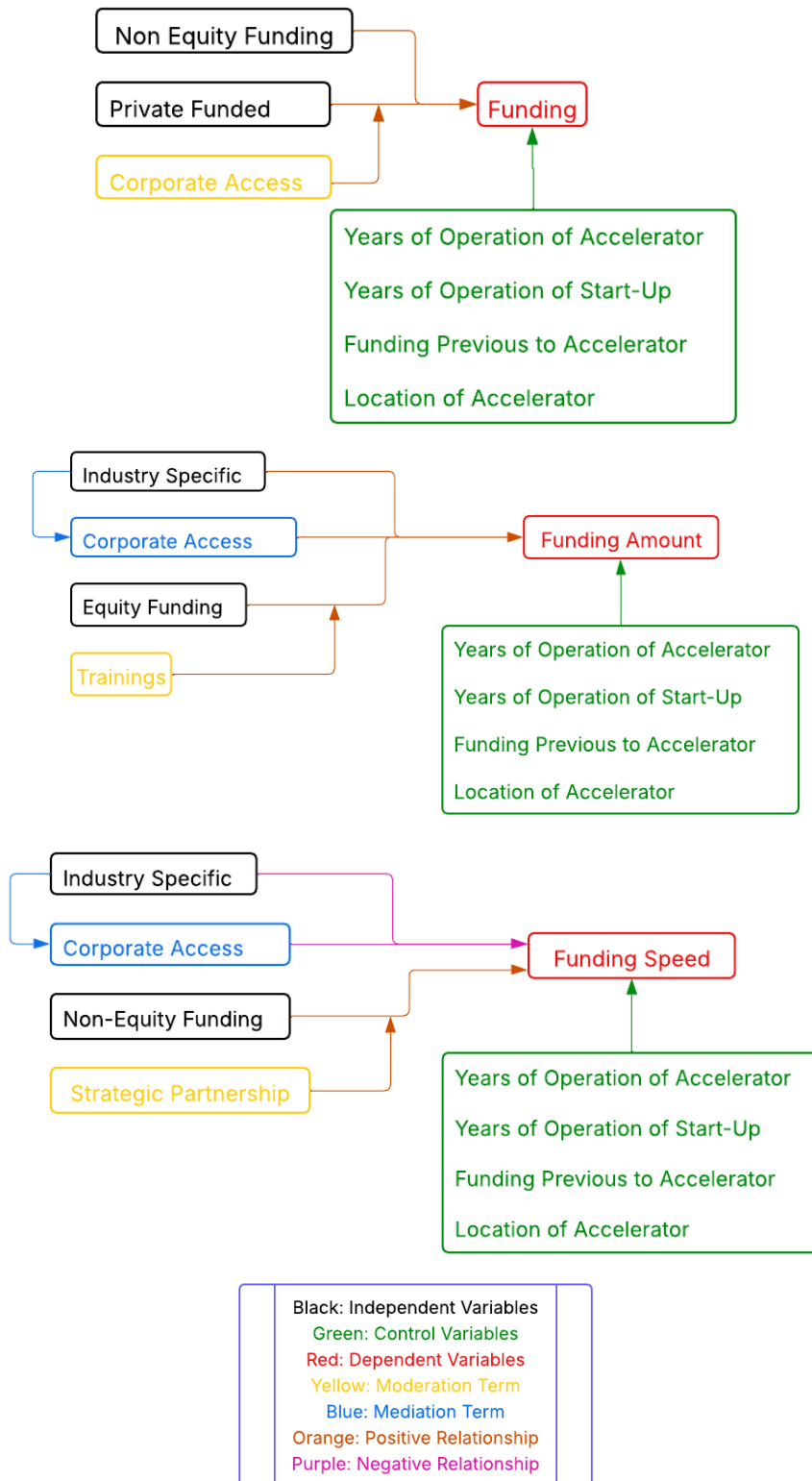


Figure 1

The next chapter will delve deeper into the data and the further context of this study.

3. Data & Sample

3.1. Accelerators of South Holland

This research focuses on accelerator programs based in the province of South Holland, a key innovation hub within the Netherlands. To identify relevant accelerators in South Holland, a comprehensive list was compiled using Dealroom, a widely recognized platform for startup and venture capital data, being used in other research as in the one of van Meeteren et al., 2022. Dealroom's classification and location filters were applied to select accelerator programs operating in the region.

Although some accelerators had no listed cohorts on Dealroom, additional sources such as official websites and public records were used to verify their activity. This ensures a balance between contextual accuracy and methodological rigor.

To reduce the risk of omission, local startup and innovation networks were manually reviewed to validate the list. While some organizations may offer acceleration-like support (e.g., YES!Delft), this study includes only those clearly identified and promoted as accelerators. The final list, based on Dealroom and external verification, is considered comprehensive and replicable, providing a solid foundation for regression analysis.

According to the website there are 30 accelerator programs. Of these, 18 accelerator programs – namely in the Appendix – were found to have associated startups confirmed, while the remainder were included – in the Appendix for accelerator characteristics analysis purposes – based on available information regarding their structure, objectives, and operational activity, even if no associated startups were listed in the database. This can be justified as according to Hochberg (2016) there are programs that discourage public reporting for competitive reasons.

3.2. Accelerator's Characteristics

In addition to identifying the accelerator programs, this research also undertakes a comparative analysis of their characteristics. Each accelerator is evaluated based on a structured set of features derived from their publicly available profiles, such as the provision of equity or non-equity funding, strategic partnerships, corporate access, training, international or local scope, and sectoral focus. This matrix of characteristics allows for a deeper understanding of the value propositions offered by each program. Furthermore, a characteristic-based analysis enhances the uniqueness of regional mapping. It allows this research to highlight specific strengths and gaps within South Holland's accelerator landscape, offering practical insights to start-up founders,

investors, and ecosystem builders. It also lays a more flexible foundation for comparing programs across regions in future studies.

Finally, it is important to note that accelerator program structures vary widely across the region. While some programs operate based on formal cohort models, where a batch of startups goes through a defined program together, others adopt more flexible or ad hoc approaches, offering training, mentoring, and funding on a rolling basis or as part of a broader ecosystem initiative. As a result, not all accelerated startups can be easily identified at the cohort level. This structural variation is considered when interpreting results and assessing the comparability of accelerator outcomes.

Many accelerators in South Holland display overlapping features, for instance, some publicly funded programs also offer equity investment or combine university affiliation with corporate partnerships. To address this complexity, the study evaluates accelerators based on their actual offerings, capturing how they function in practice, at the time of the thesis. A detailed table (Table 1) presents all these characteristics and their description. If grouping them is needed, then the first two can be referred as funding mechanisms, the following three as ownership (Drori & Wright, 2018), the next four as services and the last four as focus (Pauwels et al., 2016).

It is important to note that all these characteristics are identified, but only the ones influence the follow-on financing outcomes, based on theory and previous literature are incorporated into the main analysis.

Characteristic	Description
Equity Funding	The accelerator provides financial support to startups in exchange for equity ownership, typically as seed investment.
Non-Equity Funding	The accelerator offers funding (e.g., grants or subsidies) without requiring an ownership stake in the startup.
Government Funded	The program is primarily financed by public institutions or national/regional government bodies.
Private Funded	The accelerator is funded by private entities such as investors, corporations, or venture funds, with no public involvement.
Mixed Funded	The accelerator receives financial support from both public and private sources.
Strategic Partnership	The accelerator acts as a partner for mentorship, supports growth, offers advice, problem-solving, or co-development opportunities.
Corporate Access	The program connects startups with corporate partners to form partnerships between them, pilot programs, LoIs and further commercial opportunities for growth or validation.
Working Space	Physical office or co-working facilities are provided to startups during and/or after the program.
Trainings	Structured educational content is delivered, including workshops, seminars, or mentorship on topics like business development, pitching, and fundraising.
Industry Specific	The accelerator focuses on a particular sector (e.g., energy), tailoring resources and networks accordingly.
Uni./Res. Focus	The program is affiliated with a university or research institution and often supports science- or IP-based ventures.
Local	The accelerator primarily targets startups from the region and focuses on local economic or innovation impact.
Emerging Markets	The program is oriented toward startups operating in or serving emerging and developing economies.
Years of Operation	The number of years since the accelerator was founded.
No. of Cohorts	The total number of startups batches or cycles the accelerator has run, indicating its experience.
All variables are binary, with a value of 1 indicating that the accelerator possesses the given characteristic, and 0 otherwise. The only exceptions are the last two variables, which are continuous: Years of Operation is measured in Years, and Number of Cohorts is expressed as an Integer.	

Table 2

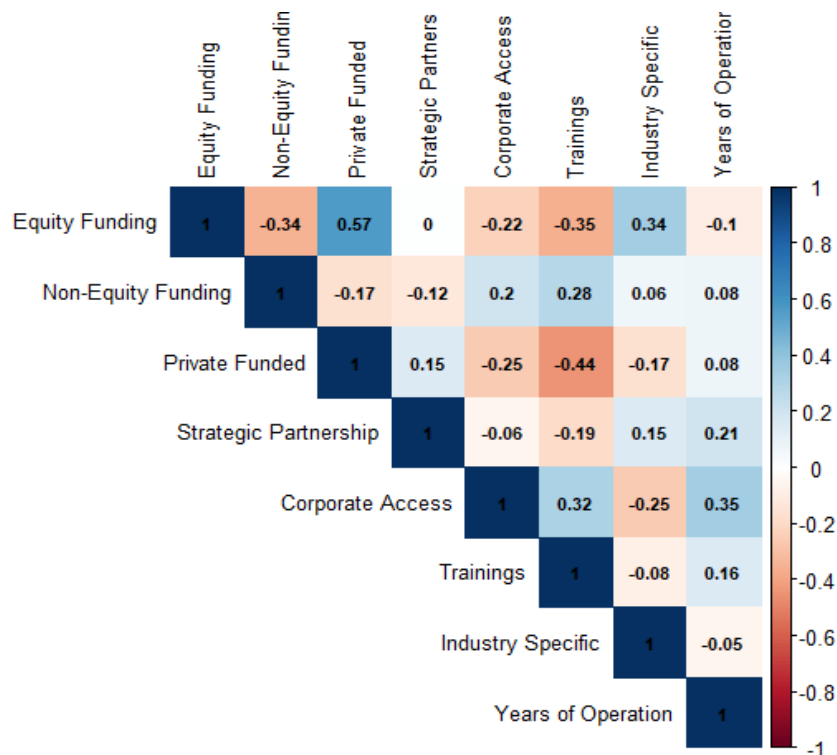
Moreover, these characteristics need to be displayed in a descriptive form to better understand the dynamics between them. The numbers are presented in Table 3 below and they refer to the 18 accelerator programs that have known accelerated startups in the database.

Characteristics \ Descriptives	No. of Obs.	Mean	Median	Std. dev.	Min	Max
Equity Funding	18	0.5	0.5	0.5145	0	1
Non-Equity Funding	18	0.3888	0	0.5016	0	1
Private Funded	18	0.3888	0	0.5016	0	1
Strategic Partnership	18	0.7777	1	0.4278	0	1
Corporate Access	18	0.4444	1	0.5113	0	1
Trainings	18	0.8888	1	0.3234	0	1
Industry Specific	18	0.3888	0	0.5016	0	1
Years of Operation of Accelerator	18	10	10	4.6653	2	17

All variables are binary, with a value of 1 indicating that the accelerator possesses the given characteristic, and 0 otherwise. The only exception is the last one, which is continuous, measured in Years.

Table 3

The above-mentioned characteristics needed to be further studied, thus a phi-coefficient Matrix is presented to show the correlations between the relationships that they have within each other – full APA Table is presented in the Appendix.



Matrix 1

3.3. Accelerated Companies

This chapter presents an overview of the startup companies included in the dataset and explains the logic behind their selection and categorization for the purposes of quantitative analysis. In total, the dataset comprises 647 companies that have participated in accelerator programs based in South Holland. These companies were identified through Dealroom and verified through additional online research. For example, manual additions were made for the non-operational companies of each accelerator, as the database allows the download only of the operational companies. So, the basic characteristics (name, location, years of operation) and the funding occurrence pre and post accelerator participation for the non-operational companies were manually added to the tested dataset.

Out of the 647 companies, 574 are currently operational, representing 88.7% of the dataset. A further 53 companies (8.2%) have been marked as closed, and 20 (3.1%) have been acquired. This distribution reflects a relatively high rate of ongoing activity, which is typical for accelerator-supported cohorts, where support services, training, and early validation may contribute to higher survival rates compared to the broader startup population.

Of the total 647 companies, 289 have known funding amounts, equating to 44.7% of the entire dataset. Since closed companies typically do not report or receive post-closure investments, funding data is primarily relevant for active startups. When considering only operational companies, 48.7% have known funding amounts.

In addition to absolute funding amounts, timing and sequencing are also critical to understanding the accelerator's impact. Out of the full dataset, 284 companies (43.9%) received funding after participating in an accelerator, while 363 companies (56.1%) did not receive any post-program funding.

An analysis of pre-acceleration funding status reveals that 529 companies (81.8%) had not received any funding before entering the accelerator, suggesting that many startups join such programs at an early developmental stage. In contrast, 118 companies (18.2%) had already secured funding prior to the program, and thus may use accelerators for scaling, networking, or strategic partnerships rather than initial financing. This distinction is crucial, as prior funding experience can influence both expectations and outcomes post-acceleration.

Among all companies with a known funding trajectory (345 in total, or 53.3% of the full dataset), a more nuanced view of post-accelerator capital flows is possible. Of these, 284 companies received funding after completing an accelerator program, while 61 companies received funding only before acceleration and did not secure additional investment afterward.

Within the group of 284 companies that secured post-acceleration funding, the most common first type of investment was Early VC funding, occurring in 169 cases. This is followed by Grant funding in 57 cases, subsequent participation in another accelerator in 37 cases, and Late VC funding in 15 cases. Interestingly, 6 companies were acquired as their first event post-acceleration, illustrating that for a small but notable number of startups, accelerator participation may have contributed directly to an exit.

Moreover, the average time it took for startups to receive their first funding post-accelerator program was approximately 15.4 months. This time window is relevant for investors and policymakers aiming to evaluate the time-to-capital of early-stage ventures. It also highlights that, although accelerators provide rapid support structures, the funding cycle continues to follow a long-term trajectory.

Of the 647 companies, 80 were found to have participated in more than one accelerator. Of these, 61 joined another accelerator after the one studied, 25 had participated in one prior, and 25 experienced acceleration both before and after the focal program. So, 55 of the 80 companies that engaged with multiple accelerators did so only once more. These patterns reflect the growing tendency among startups to treat accelerators as modular services in their broader development strategy, leveraging them at different stages for different reasons.

Furthermore, the quality and type of funding received prior to entering the accelerator were examined. Of the 118 companies that had already secured funding before participating in the studied accelerator, 88 companies (74.6%) had received VC-type funding. However, when compared to the full dataset or the companies with known funding path, this group represents only 13.6% and 25.5%, respectively, highlighting that prior VC backing remains relatively rare.

The core descriptive numbers from the information above can be summarized in the following table.

Characteristics \ Descriptives	No. of Obs.	Mean	Median	Std. dev.	Min	Max
Funding Occurrence	647	0.4389	0	0.4966	0	1
Funding Amount	284	6.8662	1	31.4536	0	431.5
Funding Speed	273	15.4261	14	9.4078	1	37
Funding Previous to Accelerator	647	0.1824	0	0.3865	0	1
Years of Operation of SU	647	8.8788	8	3.8938	1	33
Funding Occurrence and Funding Previous to Accelerator are binary values. The rest are continuous variables. Funding Amount is measured in Millions, Funding Speed in Months and Years of Operation is measured in Years.						

Table 4

It is important to note that the number of observations varies across variables, as not all variables are available for every startup in the dataset. For this reason, different sub-datasets will be used in the analysis, depending on the different dependent variables examined.

Altogether, these descriptive insights form the empirical foundation of the models developed in this thesis. They illustrate the importance of controlling for prior funding, analyzing both binary and continuous outcomes, and interpreting funding events in their temporal context. This level of detail ensures that the study captures not only whether funding occurred, but also how much, and when.

4. Methodology

4.1. Methodology

The objective of this study is to analyze how different accelerator's characteristics influence a startup's ability to attract follow-on funding. To empirically test the formulated hypotheses, a quantitative research approach is adopted. This chapter outlines the methodology used in this study.

Previous studies on accelerators and startup funding have employed a mix of qualitative and quantitative methods. Some researchers have used case studies and interviews to understand the role of accelerators (Hallen et al., 2020; Bonini & Capizzi, 2019), while others have applied econometric models to analyze large datasets (Fehder & Hochberg, 2014; Gonzalez-Uribe & Leatherbee, 2018). Studies leveraging quantitative approaches typically rely on startup funding databases to assess investment trends and accelerator effectiveness (Stayton & Mangematin, 2019). Given the focus on measuring causal relationships between participation in a program with different characteristics and funding acquisition, a quantitative approach using regression analysis is most suitable for this research.

From a methodological perspective, the use of all three indicators of startup performance as independent variables enhances construct validity and offers a richer empirical basis for identifying the best practices in accelerator design. In alignment with recent literature calling for more precise measurement of accelerator impact (Pauwels et al., 2016; Uhm et al., 2018), this framework allows also the current study to contribute both theoretically and practically to ongoing debates about how to best evaluate startup support mechanisms.

This study will use data from Dealroom, a widely recognized database tracking startup funding, accelerators, and venture capital activity globally. Dealroom offers structured data on, funding rounds, accelerator participation, along with the type of accelerator, cohort year, and funding received, company characteristics and investor data.

Simply put, the dataset used for testing links each accelerated startup with the specific characteristics of the accelerator program it attended. For example, if Startup A participated in Accelerator Program B, then the dataset reflects the features of Program B and associates them with Startup A. This integrated structure allows us to analyze how different accelerator characteristics influence startup outcomes.

The dataset will allow for empirical testing of the hypotheses by examining startups that have participated in accelerator programs with various characteristics and assessing their subsequent ability to raise money afterwards. The major variables studied are Funding, Funding Amount and Funding Speed serve as dependent

variables, on the independent variables side, different accelerator characteristics are selected.

To assess the impact of accelerator participation on follow-on funding acquisition, the study can utilize three regression analysis models. The first model is a logistic regression one, used to test Hypothesis 1 and the other two are OLS regression models for the testing of Hypothesis 2 and 3.

Model 1:

$$\begin{aligned}
 & \text{logit}(P(\text{Funding}_i = 1)) \\
 & = \beta_0 + \beta_1 \times \text{Non - Equity Funding}_i + \beta_2 \times \text{Private Funded}_i \\
 & + \beta_3 \times \text{Corporate Access}_i \\
 & + \beta_4 \times (\text{Private Funded}_i \times \text{Corporate Access}_i) \\
 & + \sum_{j=1}^n \gamma_j \text{Control Variables}_{ij}
 \end{aligned}$$

Where:

Funding: Binary, 1 if a startup raises follow-on financing within three years post-acceleration, 0 otherwise. This variable represents the core outcome of interest: whether a startup secures funding after participating in an accelerator program. It provides a direct measure of investment success post-acceleration.

Accelerator Characteristics: Binary, in this case – Non-Equity Funding, Private Funded, Corporate Access, and the intersection of the last two – these variables describes if a program offers or not these characteristics. Different and overlapping characteristics are presented for every program.

Control Variables: This can be categorized into two sections the startup one and the accelerator one. The first one includes the startup age, measured as the number of years since founding, and previous funding rounds, which capture prior investments received. These control variables help isolate the effect of accelerator participation from other factors that influence funding success. Where the second one includes the reputation of the accelerator, measured by the years of operation, the length of time the accelerator has been active and the location of the accelerator.

β coefficients: Each represent the effect of an independent variable on the likelihood of securing funding.

γ coefficients: Each represent the effect of a control variable on the likelihood of securing funding.

Model 2:

$$\begin{aligned}
& \log(\text{Funding Amount}_i + 1) \\
&= \beta_0 + \beta_1 \times \text{Industry - Specific}_i + \beta_2 \times \text{Corporate Access}_i \\
&+ \beta_3 \times (\text{Industry - Specific}_i \times \text{Corporate Access}_i) \\
&+ \beta_3 \times \text{Equity Funding}_i + \beta_4 \times \text{Trainings}_i \\
&+ \beta_5 \times (\text{Equity Funding}_i \times \text{Trainings}_i) \\
&+ \sum_{j=1}^n \gamma_j \text{Control Variables}_{ij}
\end{aligned}$$

Where:

Funding Amount: Numerical, represents the amount that the SU has received post accelerator program. The logarithm of the funding amount, is used to normalize the right-skewed distribution of funding data, mitigate the influence of extreme outliers, while improving the interpretability and statistical validity of the regression results.

Accelerator Characteristics: Binary, in this case – Industry-Specific, Corporate Access, the intersection of the last two, Equity Funding, Trainings and the intersection of the last two – these variables describes if a program offers or not these characteristics. Different and overlapping characteristics are presented for every program.

The rest are the same as above.

Model 3:

$$\begin{aligned}
& \text{Funding Speed}_i \\
&= \beta_0 + \beta_1 \times \text{Industry - Specific}_i + \beta_2 \times \text{Corporate Access}_i \\
&+ \beta_3 \times (\text{Industry - Specific}_i \times \text{Corporate Access}_i) \\
&+ \beta_4 \times \text{Non - Equity Funding}_i + \beta_5 \times \text{Strategic Partnership}_i \\
&+ \beta_6 \times (\text{Non - Equity Funding}_i \times \text{Strategic Partnership}_i) \\
&+ \sum_{j=1}^n \gamma_j \text{Control Variables}_{ij}
\end{aligned}$$

Where:

Funding Speed: Numerical, represents how fast in months the SU has received funding post accelerator program. In this case using the logarithm is not needed.

Accelerator Characteristics: Binary, in this case – Industry-Specific, Corporate Access, their intersection, and Non-Equity Funding, Strategic Partnership and their as well – these variables describes if a program offers or not these characteristics. Different and overlapping characteristics are presented for every program.

The rest are the same as above.

Control Model:

$$\begin{aligned} & \text{logit}(P(\text{Funding}_i = 1)) / \log(\text{Funding Amount}_i + 1) / \text{Funding Speed}_i \\ & = \sum_{j=1}^n \gamma_j \text{Control Variables}_{ij} \end{aligned}$$

All are explained above.

Before testing each *Hypothesis* in all cases, a control model is tested, so after that differences between the control model and the tested model can be checked and interpreted.

Full Model:

$$\begin{aligned} & \text{logit}(P(\text{Funding}_i = 1)) / \log(\text{Funding Amount}_i + 1) / \text{Funding Speed}_i \\ & = \sum_{k=1}^m \beta_k \text{All Independent Variables}_{ik} + \sum_{j=1}^n \gamma_j \text{Control Variables}_{ij} \end{aligned}$$

All are explained above.

After testing each *Hypothesis* in all cases, a full model is tested, so after that differences between the tested model and the full model can be checked and interpreted.

ANOVA Test:

In order to evaluate these differences and whether the inclusion of more accelerator characteristics significantly improves the model's explanatory power, an ANOVA (Analysis of Variance) test is conducted by comparing a baseline model containing only control variables to a full model that includes both control and independent variables.

The following elements from the ANOVA output are interpreted.

ANOVA Outputs	Description
Residual Degrees of Freedom (Res.Df)	This reflects the number of observations minus the number of estimated parameters in the model. A reduction in Res.Df from the control to the full model indicates the inclusion of additional predictors.
Residual Sum of Squares (RSS)	This quantifies the total unexplained variance in the dependent variable. A lower RSS in the full model suggests improved fit because of the new explanatory variables.
Sum of Squares (Model Difference)	This value represents the difference in RSS between the two models and captures the additional variation explained by the added variables in the full model.
F-statistic	The F-value assesses whether the reduction in unexplained variance due to the new variables is significant relative to the increase in model complexity.
p-value (Pr(>F))	This tests the null hypothesis that the additional variables in the full model do not improve the model fit beyond what is explained by the control variables.

Table 5

This test supports the model validation process by quantifying the contribution of the added accelerator characteristics to the explanatory power of the regression models. By testing the difference in explained variance between the two models, the ANOVA test provides statistical justification for the relevance of the hypothesized predictors and helps confirm that observed effects are not solely attributable to the control factors.

According to Dealroom, there are 30 different accelerator companies in the region of South Holland, and this research will utilize data from 18 of them to conduct the analysis. Meaning data about funding will be drawn about all the companies known to the database that have been accelerated from these companies. The dataset spans multiple years to ensure a robust and representative sample.

For each one of the different accelerator companies the database provides distinct information about every company that participated in all the cohorts. The information ranges from general knowledge such as founding year and location to more in-depth financial metrics such as funding rounds and dates of them or even metrics that are not relevant for this study such as social media links, revenue and valuation.

Before conducting the analysis, the dataset underwent data preprocessing, including clustering to classify accelerators based on shared characteristics such as funding size, mentorship intensity, and investor networks. Clustering serves as a preprocessing step

to ensure the validity of accelerator classifications before statistical testing. Handling missing data is another important aspect of data preparation. Some Dealroom variables are marked as “NA”, which could affect the integrity of the regression models. Observations with excessive missing data are excluded from specific models to prevent distortions in results.

Having said that, this study will provide an empirical validation of the formulated hypotheses and contribute to the literature by offering a data-driven evaluation of accelerator effectiveness.

4.2. Analysis' Map

Before moving on and to facilitate a clear understanding of the empirical investigation, the following analysis map presents a structured overview of the key constructs, hypothesized relationships, and how they are going to be treated into the analysis that is guiding this study.

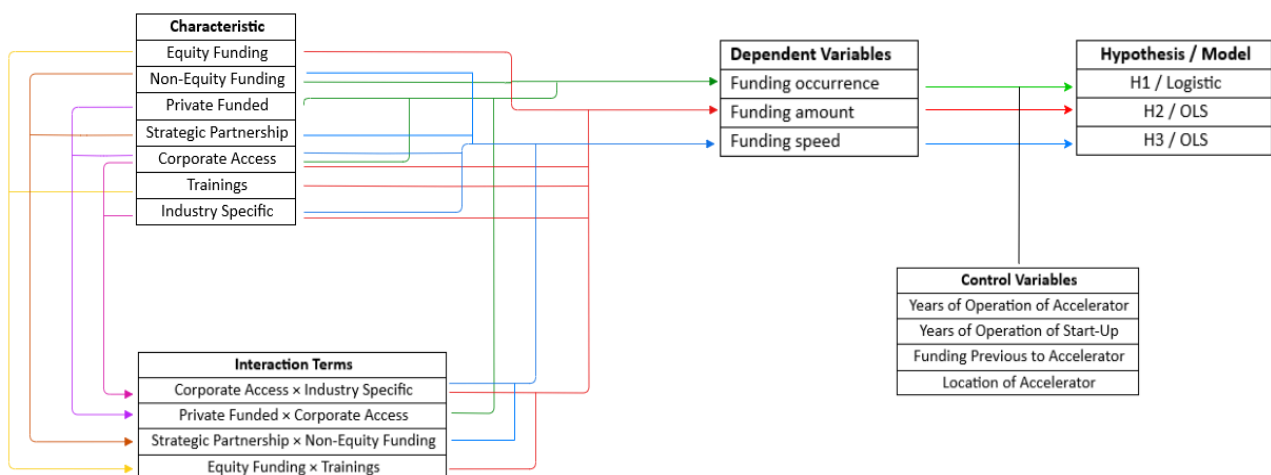


Figure 2

5. Results

5.1. Findings

This chapter presents the outcomes of the models introduced in the previous chapter, examining the relationship between accelerator characteristics and the 3 dependent variables and comments on their results. The tables below present the results of the control, the hypothesized and the full model for each of the dependent variables.

Although the full regression model, in some cases, shows improved statistical significance for certain variables, the primary focus of the analysis remains on testing theoretically grounded hypotheses. The hypothesis-only model is mostly used in the main text to preserve conceptual clarity and maintain alignment with the research design. Prioritizing the variables derived from the theoretical framework the empirical analysis stays focused on the core research questions, rather than being driven solely by statistical outcomes. At the same time, the control and full model are included to provide a broader perspective and to demonstrate the robustness of the findings. In cases where the full model yields stronger or additional statistically significant results, these are briefly discussed in the main text to offer further insights, while acknowledging that such findings may be exploratory in nature and require additional theoretical interpretation. Also, the changes in the correlations between models are also discussed and justified. This approach balances theory-driven analysis with statistical rigor and transparency.

5.1.1. Funding Occurrence

Table 6 below presents the results of the analysis done concerning the Funding Occurrence. After the table comments for the results are presented.

Results - Funding Occurrence ₁			
	Control Model	Hypothesized Model	Full Model
(Intercept)	0.12	1.66* [0.42, 6.54]	0.12
Years of Operation Accelerator	0.58***	1.07* [1.01, 1.14]	0.58***
Years of Operation SU	0.94**	0.95 [†] [0.91, 1]	0.94**
Funding Previous to Accelerator	1.93**	1.38 [0.88, 2.15]	1.93**
Accelerator Location: Rotterdam	0.83***	0.53 [†] [0.25, 1.11]	0.83***
Accelerator Location: The Hague	0.49***	0.26** [0.11, 0.64]	0.49***
Non-Equity Funding (H1a)		1.04 [†] [0.63, 1.73]	0.06***
Private Funded (H1b)		0.16*** [0.05, 0.47]	< 0.01***
Corporate Access (H1b)		0.90 [0.36, 2.24]	0.80***
Private Funded : Corporate Access (H1b)		3.41* [1.37, 11.29]	3.15***
Industry Specific			0.04
Trainings			0.2
Equity Funding			3.6***
Strategic Partnership			2.58
Government Funded			0.52**
Working Space			0.02***
University/Research Focus			1.15***
Local			0.14
Emerging markets			2.36***
Num. of Obs.	592	592	592
McFadden R ²	0.11	0.08	0.11
Covariance Type	Robust	Robust	Robust
<p>This Table represents the effects of the accelerator characteristics on follow-on funding occurrence. Hypothesized estimates are based on model 1 presented in the Methodology chapter. Control and full estimates are based on the control and full models presented in the Methodology chapter as well. The first five characteristics described correspond to the control variables of each model.</p> <p>***p < 0.001, **p < 0.01, *p < 0.05, †p < 0.1</p> <p>1. Odds Ratios reported. Confidence Intervals in brackets – only for hypothesized results.</p>			

Table 6

Starting with examining the factors influencing whether a startup secures funding, a series of logistic regression models were estimated. Firstly, a control model is tested – something that happened for every hypothesis, as described in the methodology chapter – including, years of operation at the time of acceleration (both for the startup and the accelerator), prior funding history, and location dummies. Results show that the number of years a startup has been active negatively impacts the probability of securing follow-on funding ($\beta = -0.054$, $p = 0.027$), whereas the number of years an accelerator has been operating positively correlates with funding likelihood ($\beta = 0.118$,

$p < 0.001$). Startups that were funded before entering the accelerator have a marginally significant higher chance of securing post-program funding ($\beta = 0.368$, $p = 0.096$). These controls suggest that organizational maturity and early validation are predictive of future funding success.

Adding the main explanatory variables: Non-Equity Funding, Private Funded, and Corporate Access. The coefficient for participation in non-equity funding programs is positive ($\beta = 0.291$, OR = 1.04), indicating an increase in the odds of securing follow-on funding, though the effect is marginally significant ($p = 0.096$). Despite that Hypothesis 1a is supported, and it aligns with the economic reasoning provided. The result is consistent with recent literature highlighting non-equity programs as more attractive to early-stage startups (e.g., Hallen et al., 2020). However, in the full model, its odds ratio drops significantly, suggesting that non-equity funding may in fact be detrimental when controlling for all other program characteristics. This shift likely reflects confounding in the hypothesized model, where the positive or neutral impact of other co-varying features (such as equity support or mentorship) obscures the standalone effect of non-equity structures. The full model reveals that, once these influences are accounted for, non-equity funding may signal lower resource commitment or support intensity, thereby reducing investor confidence.

Introducing the interaction between Private Funded and Corporate Access to test Hypothesis 1b. The interaction term is statistically significant ($\beta = 1.688$, $p = 0.028$), with an odds ratio of 3.41, suggesting that within privately funded programs, the presence of corporate access markedly improves the likelihood of startups securing follow-on funding. This supports Hypothesis 1b and reinforces the economic rationale based on resource-based theory that corporate partnerships in private accelerators may compensate for lack of public legitimacy by offering superior industry networks and value-added resources (Seitz et al., 2024).

Interestingly, the main effect of Private Funded is now highly negative ($\beta = -1.8343$, $p < 0.001$), meaning that in the absence of corporate access, private accelerators are significantly less likely to help startups secure funding. The intensification of this negative effect suggests that the full model is controlling for variables that had previously masked the underlying disadvantage associated with private funding. One interpretation is that privately funded accelerators may lack the structure, reputation, or public support mechanisms that increase startup visibility or credibility in the eyes of investors. Corporate Access alone has a negative but insignificant coefficient ($\beta = -0.102$, $p = 0.826$), suggesting that its positive effect is conditional on the funding structure of the accelerator. In both the hypothesized and full models, this interaction shows that startups in privately funded accelerators with corporate access are significantly more likely to receive funding, with odds ratios above 3. The interaction term effectively captures this conditional mechanism. These findings align with the logic that corporate access adds substantial value in private contexts where public

signaling is absent. The economic logic is that privately funded accelerators lack inherent government legitimacy but can compensate through strong industry ties.

The control variables maintain their significance and direction. Prior funding is now significant at the 5% level ($\beta = 0.4645$, $p = 0.0407$), reinforcing its role as a strong predictor. ANOVA comparison with the baseline model reveals that the addition of these accelerator characteristics significantly improves model fit ($\Delta\text{Deviance} = 27.11$, $df = 4$).

Lastly, a full model is tested, including a comprehensive set of accelerator characteristics and the same interaction term. Equity funding emerges as one of the strongest predictors of funding success, with an odds ratio of 3.6, reinforcing its role as a key support mechanism that aligns the interests of accelerators and startups and attracts investor attention. The interaction between Private Funded and Corporate Access remains strongly positive and significant ($\beta = 27.295$, $p < 0.001$), confirming again Hypothesis 1b.

However, many coefficients in this full model are extremely large or small, likely due to limited variation among certain variables, where certain predictor variables perfectly predict the outcome, leading to inflated or undefined coefficient estimates.

Statistically, the changes stem from the inclusion or exclusion of confounding or suppressing variables, as well as the presence of interaction effects. For example, the negative impact of private funding becomes far more pronounced in the full model, suggesting that other characteristics — such as equity support or strategic partnerships — may have partially masked its true effect when not accounted for. In cases like the dramatic drop in the odds ratio of non-equity funding or the extreme result for working space ($OR = 0.02$), such patterns may reflect quasi-complete separation or data sparsity, which in turn can inflate or suppress coefficients artificially. These outcomes do not invalidate the findings but suggest the need for cautious interpretation, which can be done from the theoretical lens of the Resource-Based View (RBV).

These shifts underscore the fundamental idea that resources do not operate in isolation, but gain strategic value through complementarity and configuration. The finding that private funding alone reduces the likelihood of follow-on funding, but its negative effect is reversed when paired with corporate access, exemplifies this RBV logic: it is not the mere possession of a resource (funding structure), but its integration with relational and network-based capabilities (e.g., corporate access) that creates value. Similarly, the delayed emergence of significance for corporate access in the full model supports the RBV proposition that organizational resources are context-dependent — their contribution to competitive advantage (or in this case, funding success) depends on how they are embedded within the firm's broader resource portfolio. The changing correlations thus reflect not only empirical sensitivity but also

offer substantive theoretical support for the RBV: value arises from bundles of resources and capabilities, not from individual features considered in isolation.

In sum, the observed changes in coefficients across models highlight both the complexity of accelerator design and the importance of resource combinations. While such results are statistically possible, model's assumptions should be interpreted with caution, but the key substantive conclusion remains intact.

5.1.2. Funding Amount

Table 7 below presents the results of the analysis done concerning the Funding Amount. After the table comments for the results are presented.

Results - Funding Amount ₁			
	Control Model	Hypothesized Model	Full Model
(Intercept)	1.8 [†] (0.37)	1.8 (0.68)	0.01 ^{***} (0.95)
Years of Operation Accelerator	1 (0.02)	1 (0.03)	1.1 (0.08)
Years of Operation SU	1.1 ^{**} (0.02)	1.1 [*] (0.03)	1.1 [*] (0.03)
Funding Previous to Accelerator	1 (0.14)	1 (0.16)	1.1 (0.17)
Accelerator Location: Rotterdam	0.5 ^{**} (0.21)	0.5 ^{***} (0.22)	1.2 (0.35)
Accelerator Location: The Hague	0.6 [†] (0.24)	0.6 (0.39)	0.2 (1.17)
Corporate Access (<i>H2a</i>)		1.7 [*] (0.31)	1.1 (0.3)
Industry Specific (<i>H2a</i>)		1.5 (0.36)	0.9 (0.55)
Industry Specific : Corporate Access (<i>H2a</i>)		0.5 (0.71)	0.1 [†] (1.27)
Trainings (<i>H2b</i>)		1 [*] (0.32)	3.6 ^{**} (0.52)
Equity Funding (<i>H2b</i>)		0.8 (0.4)	11.8 ^{**} (0.86)
Non-Equity Funding			2.2 ^{***} (0.28)
Private Funded			0.4 (1.06)
Strategic Partnership			1.9 [*] (0.32)
Government Funded			1.5 (0.4)
Working Space			0.2 ^{***} (0.31)
University/Research Focus			1.5 ^{**} (0.32)
Local			0.7 (0.64)
Emerging markets			5.1 [†] (0.94)
Num. of Obs.	288	288	288
Adjusted R ²	0.06	0.08	0.09
RSE	1.08	1.07	1.06
F-statistic	4.51	3.31	2.54
Covariance Type	Robust	Robust	Robust
<p>This Table represents the effects of the accelerator characteristics on follow-on funding amount. Hypothesized estimates are based on model 2 presented in the Methodology chapter. Control and full estimates are based on the control and full models presented in the Methodology chapter as well. The first five characteristics described correspond to the control variables of each model.</p> <p>***p < 0.001, **p < 0.01, *p < 0.05, †p < 0.1</p> <p>1. Exponentiated Coefficients reported. Robust standard errors in parentheses.</p>			

Table 7

Moving on to how specific accelerator characteristics influence the total amount of funding secured by startups after completing an accelerator program. The dependent variable is a natural logarithm of the total post-accelerator funding amount raised, allowing for interpretation also in multiplicative percentage terms. Three models were estimated. To begin with, the control model reveals that the number of years a startup has been operating prior to acceleration significantly increases the total amount of

funding raised ($\beta = 0.058$, $p < 0.01$). Interestingly, an accelerator program being located in Rotterdam or The Hague is associated with significantly less funding compared to the base city (Delft).

In line with Hypothesis 2a, which posits that accelerators combining industry-specific focus with corporate access lead to higher funding amounts, the individual effects of Corporate Access ($\beta = 0.546$, $p \approx 0.08$) and Industry Specificity ($\beta = 0.417$, $p = 0.25$) show positive but statistically weak associations. The presence of corporate access alone increases funding by approximately 72.6%, but loses significance once additional variables are introduced in the full model, and industry-specific orientation by 51.8%, though only the former reaches marginal significance.

However, the interaction term between Corporate Access and Industry Specificity is negative ($\beta = -0.605$, $p = 0.40$), suggesting that the simultaneous presence of both characteristics may offset each other and lead to diminishing returns. The lack of statistical significance in the hypothesized model changes in the full model. From an economic reasoning perspective, while corporate access provides linkages to customers and investors and industry-specific design targets sector-relevant skills and networks, the combination may limit startup flexibility or result in narrow applicability of resources.

Moreover, Hypothesis 2b, which argues that equity-funded accelerators combined with intensive training yield higher total funding, is not supported. While the individual effect of Equity Funding is negative ($\beta = -0.201$, $p = 0.62$), Trainings show a small, positive coefficient ($\beta = 0.034$, $p = 0.93$), but neither is significant, and the interaction term is dropped due to collinearity. These results indicate no strong evidence for the synergy between equity provision and training intensity in this specification. Notably, these effects were muted or absent in the hypothesized model, likely due to confounding relationships with other unobserved program characteristics. The fact that they become highly significant only in the full model highlights the importance of accounting for overlapping resource configurations, and supports the RBV argument that resources derive their value through context-specific bundling.

The ANOVA comparison between the control model and test model ($F(5, 277) = 2.03$, $p \approx 0.07$) suggests a marginal improvement in model fit, indicating modest explanatory power added by the accelerator features.

In this case, the full model reveals several notable findings. Equity Funding shows a strong and significant positive coefficient ($\beta = 2.76$, $p < 0.01$). This stark contrast with earlier models reflects the influence of omitted variable bias when other funding types and program characteristics are excluded – but better represents real world scenarios. Non-Equity Funding is also positively significant ($\beta = 1.165$, $p < 0.01$), corresponding to a big increase.

Additional support is found for Strategic Partnership ($\beta = 0.653$, $p < 0.05$) and Trainings ($\beta = 1.716$, $p < 0.01$), which align with resource-based theory and suggest that programs embedding structured knowledge transfer or offering smart capital perform well. These results can lead to indirect support to Hypothesis 2b, although the interaction term between Trainings and Equity Funding was excluded due to multicollinearity, preventing direct testing.

Interestingly, the interaction term for Corporate Access \times Industry Specific is again negative and large ($\beta = -2.42$, $p \approx 0.06$), and marginally significant this time, suggesting strong evidence of a potential trade-off when both features are combined—perhaps because resource specificity and corporate goals may misalign or impose constraints. This provides partial empirical backing for rejecting Hypothesis 2a as initially posited.

The overall R^2 increases from the control model to the full model, with an F-test suggesting statistically significant improvement. While this indicates a relatively low proportion of variance explained, such figures are typical for models predicting financial outcomes, which are often influenced by external macroeconomic and sector-specific factors. Also, the possibility of multicollinearity among accelerator characteristics may be inflating standard errors and obscuring true effects in intermediate models.

The shifts observed in the magnitude, direction, and significance of predictor variables across the control, hypothesized, and full models warrant careful interpretation. These changes are not anomalies but reflections of the complex and interrelated nature of accelerator characteristics. For example, programs offering equity funding often also provide training or corporate access, making it difficult to isolate the unique contribution of each characteristic in limited models. As such, coefficients in the control and hypothesized models may be biased due to omitted variable bias, overstating or understating the role of individual predictors.

One clear illustration of this dynamic is the change in the effect of corporate access, which is modestly significant in the hypothesized model but loses statistical significance in the full model. This shift suggests that the effect of corporate access may be confounded by other program features. Similarly, the dramatic increase in the effect of equity funding — from non-significance in the hypothesized model to a highly significant and large positive effect in the full model — is a case of suppression. When other overlapping variables are controlled for, the unique contribution of equity funding becomes more visible. These changes highlight the importance of interpreting effects within a fully specified context.

From the perspective of Resource-Based View (RBV) theory, these changing relationships strongly reinforce the foundational idea that the value of resources is context-dependent and synergistic. In RBV, competitive advantage arises not simply

from possessing individual resources (e.g., funding, space, training), but from how these resources are configured, bundled, and deployed. The positive and growing impact of training and equity funding in the full model exemplifies how certain resources become more valuable when understood within a broader resource system. Conversely, the declining significance of corporate access or industry specificity once other variables are introduced suggests that these features may only contribute value when combined with complementary assets. This aligns with the RBV principle that resource effects are rarely additive — their impact emerges through interdependence, not isolation.

The observed changes also demonstrate how non-valuable or non-rare resources may not contribute to outcomes, despite being offered. In RBV terms, such resources fail the “VRIN” test (Valuable, Rare, Inimitable, and Non-substitutable). Therefore, the evolution of effects across models does not only represent statistical nuance but provides empirical evidence for the theoretical claim that startup success depends not on singular accelerator characteristics, but on the strategic orchestration of multiple capabilities.

All in all, hypothesis 2 shows interesting findings. The full model, by capturing these interactions more comprehensively, allows us to draw conclusions that are not only statistically sound but also theoretically grounded in the resource-based logic of competitive advantage.

5.1.3. Funding Speed

Table 8 below presents the results of the analysis done concerning the Funding Occurrence. After the table comments for the results are presented.

Results - Funding Speed ₁			
	Control Model	Hypothesized Model	Full Model
(Intercept)	10.76*** (2.73)	10.69* (5.13)	8.76 (13.53)
Years of Operation Accelerator	-0.01 (0.18)	1 (0.03)	-0.90 (0.60)
Years of Operation SU	0.93*** (0.15)	1.1* (0.03)	1.00*** (0.16)
Funding Previous to Accelerator	-6.09*** (1.23)	1 (0.16)	-5.76*** (1.47)
Accelerator Location: Rotterdam	-3.17 (2.14)	0.5*** (0.22)	-1.96 (4.01)
Accelerator Location: The Hague	-0.36 (1.98)	0.6 (0.39)	-0.36 (1.98)
Corporate Access (H3a)		-0.73 (2.83)	6.25 (5.27)
Industry Specific (H3a)		-1.88 (2.93)	19.83* (8.70)
Industry Specific : Corporate Access (H3a)		7.79 [†] (4.05)	
Non-Equity Funding (H3b)		-8.88 [†] (5.22)	-7.84 [†] (4.50)
Strategic Partnership (H3b)		-4.68 (4.86)	-4.13 (4.99)
Strategic Partnership : Non-Equity Funding (H3b)		12.00* (5.75)	
Private Funded			20.36 [†] (11.50)
Trainings			1.98* (10.37)
Government Funded			-9.37* (4.60)
Working Space			8.04 (5.01)
University/Research Focus			6.28* (2.69)
Local			-3.79 (4.65)
Emerging markets			-4.58 (10.14)
Num. of Obs.	273	273	273
Adjusted R ²	0.17	0.17	0.18
RSE	8.64	8.64	8.62
F-statistic	12.4	6.15	4.67
Covariance Type	Robust	Robust	Robust

This Table represents the effects of the accelerator characteristics on follow-on funding speed. Hypothesized estimates are based on model 3 presented in the Methodology chapter. Control and full estimates are based on the control and full models presented in the Methodology chapter as well. The first five characteristics described correspond to the control variables of each model.

***p < 0.001, **p < 0.01, *p < 0.05, †p < 0.1

1. Standard Coefficients reported. Robust standard errors in parentheses.

Table 8

Lastly, evaluating the influence of accelerator characteristics on the time it takes for startups to secure follow-on funding, three OLS models are tested. First of all, the control model shows that the number of years the startup had operated prior to acceleration is a strong predictor of speed, with each additional year is associated with approximately 0.93 units faster time to funding ($\beta = 0.932$, $p < 0.001$). Additionally, prior funding negatively predicts speed ($\beta = -6.0911$, $p < 0.001$), meaning startups that

had already received funding take significantly longer post-acceleration to obtain their next round. This could be due to longer negotiation cycles for larger funding rounds.

Furthermore, four main program characteristics—Industry Specific, Corporate Access, Strategic Partnership, and Non-Equity Funding— were introduced as well as their interactions: Industry Specific \times Corporate Access and Strategic Partnership \times Non-Equity Funding, tested in hypothesis 3a and 3b, respectively. The model fit slightly improves ($R^2 = 0.226$ vs. 0.188), although the F-test comparison is not significant ($p = 0.455$), indicating limited overall explanatory gain.

Looking at Hypothesis 3a, a positive and marginally significant interaction effect ($\beta = 7.791$, $p = 0.056$) is observed for the interaction term. This suggests that the combined presence of both features unexpectedly speeds up funding, opposite with the hypothesis. The interpretation aligns with economic reasoning as such accelerators may offer deep sectoral integration and long-term collaboration opportunities, they also open the doors to targeted investors, reducing the post-program negotiation timeline.

Looking at Hypothesis 3b, the interaction term between Strategic Partnership and Non-Equity Funding is positive and statistically significant ($\beta = 11.996$, $p = 0.038$), indicating that such programs indeed accelerate funding speed. This may be due to the role these strategic alliances play to investors, coupled with the flexibility and non-dilutive nature of the funding model. Startups in these environments might face fewer constraints and faster go-to-market cycles.

Finally, in the full specification model (Model 3 Full), which includes all accelerator characteristics and controls, the interaction terms are no longer estimable due to multicollinearity or perfect prediction, as evidenced by NA coefficients. While the expanded model improves R^2 only slightly (to 0.226) and does not offer a statistically significant improvement in fit over the simpler model ($p = 0.249$), several insights remain consistent. The years of operation of the startup ($\beta = 0.9990$, $p < 0.001$) and prior funding ($\beta = -5.7621$, $p < 0.001$) remain significant predictors of speed. Notably, Industry Specific and University/Research Focus are now significant on their own ($p < 0.05$ and $p < 0.1$ respectively), suggesting that specialized and academically affiliated accelerators might influence funding timelines independently.

The differences observed between the hypothesized and full models reveal important insights into both the complexity of real-world accelerator programs and the applicability of the Resource-Based View (RBV). The changes are not merely statistical fluctuations but rather evidence of the interconnected nature of accelerator characteristics. For example, corporate access, non-equity funding, and industry specificity each exhibit unstable effects across model specifications, suggesting that their impact is context-dependent and sensitive to how other resources are modeled.

From the perspective of the Resource-Based View (RBV), the changing relationships across models underscore one of the theory’s central tenets: the value of a resource is contingent on how it is configured and combined with other resources. Resources such as strategic partnerships, industry specificity, or corporate access do not inherently accelerate or delay funding outcomes — their impact depends on the resource context in which they are embedded. This supports the RBV argument that competitive advantage arises not from isolated resources, but from unique and coherent resource configurations that are valuable, rare, and difficult to replicate.

In summary, the variation in coefficient behavior across models both reflects the complexity of accelerator program structures and reinforces theoretical expectations from RBV. While some of the changes point to statistical challenges and data limitations, they also reveal that the strategic value of accelerator features is not fixed. As such, a deeper understanding of resource orchestration is essential for both academic theory-building and practical accelerator design. All in all, the results provide empirical support for Hypothesis 3b, where strategic non-equity accelerators reduce the time to funding. Hypothesis 3a is not supported, as a marginally significant acceleration is observed in dual industry-specific and corporate access settings.

5.2. Analysis Summary

All the above interpreted results show the influence of accelerator characteristics on three distinct startup funding outcomes: funding occurrence, total amount raised, and speed of funding, corresponding to Hypotheses 1, 2, and 3 respectively. Collectively, the analysis highlights the conditional and multifaceted role of accelerator design, as reflected in the matrix below summarizing whether each sub-hypothesis was supported.

Model	Hypothesis	Dependent Var.	Independent Var.	Conclusion
1	H1a	Funding	Non-Equity Funding	Marginally Supported
1	H1b	Funding	Private Funded, Corporate Access	Strongly Supported
2	H2a	Funding Amount	Industry Specific, Corporate Access	Not Supported
2	H2b	Funding Amount	Equity Funding, Trainings	Directionally Supported
3	H3a	Funding Speed	Industry Specific, Corporate Access	Not Supported
3	H3b	Funding Speed	Non-Equity Funding, Strategic Partnership	Supported

Table 9

All these findings underscore the importance of considering both individual and combined effects of accelerator characteristics, and the role of complementarities or conflicts between them.

6. Discussion & Conclusion

6.1. Discussion

6.1.1. Connecting with Literature

This research contributes to the understanding of how specific accelerator characteristics influence three distinct dimensions of startup follow-on funding outcomes: the likelihood of securing funding, the amount of funding raised, and the speed at which funding is obtained. Through a structured series of regression models, several insights emerge that both confirm and challenge prior literature. The added value of this thesis lies in its granular examination of accelerator design features, its use of interaction effects, while incorporating economic reasoning and theory-driven hypotheses.

Recently, Hallen et al. (2020) suggest that non-equity programs are particularly attractive to early-stage ventures due to their non-dilutive structure, allowing startups to retain control and appeal to risk-averse or mission-driven founders. This study extends that insight by proposing that this characteristic also increases the likelihood of follow-on funding. This aligns with Kaplan & Strömberg (2003) argument that founders optimize for capital that minimizes agency costs and control loss. It also dovetails with recent counter-signaling findings in the accelerator domain - top entrepreneurs may avoid equity-taking accelerators to signal quality (Browne et al., 2024). This implies that non-equity programs can attract higher-potential ventures that eschew equity deals, potentially resulting in stronger funding outcomes. This effect reinforces the broader economic logic that founders respond strategically to funding design. Non-equity programs often appeal to early-stage startups that are particularly resource-constrained and risk-averse toward equity dilution, viewing such models as an opportunity to access external value without sacrificing ownership.

While Seitz et al. (2024) and Drori & Wright (2018) focus on the stand-alone advantages of corporate accelerators, few studies have explicitly tested whether corporate access in privately funded programs can offset the absence of public legitimacy (Pauwels et al., 2016). This study confirms the theoretical rationale (legitimacy and access to institutional networks) (Clarysse & Yusubova, 2014) and the resource-based view (strategic resource bundling) (Yi et al., 2016). The findings show that private accelerators with corporate access significantly enhance funding success - specifically, private programs with extensive corporate involvement are associated with 3.4 times higher odds of startup funding success. This conditional effect represents a key contribution of this study. It adds nuance to the growing body of research on the hybridization of accelerator models by illustrating how blending

resource-based advantages can improve venture performance (Seitz et al., 2024; Kanbach & Stubner, 2016).

Furthermore, the contrast in outcomes between privately funded programs with and without corporate access underscores a critical design insight. Privately funded accelerators must offer value substitutes for the legitimacy typically conferred by government backing (Pauwels et al., 2016). This reinforces the RBV argument that resource bundling and complementarity, in this case, private capital paired with corporate relational assets, can offset the liabilities associated with limited public legitimacy (Seitz et al., 2024). Unlike government-backed accelerators, privately funded ones lack inherent signaling power. However, when coupled with corporate partners, they can offer access to tacit market knowledge, reputational capital, and strategic introductions, which are difficult for startups to obtain independently (Cohen et al., 2019). This thesis is among the first to quantitatively validate this claim using interaction terms, a methodological approach that strengthens the explanatory power of previous models. It also aligns with the dynamic capabilities' extension of RBV, suggesting that accelerators can act as intermediaries that reconfigure startup resource bases through tailored alliances.

The control variables behaved as expected and offered insight into startup maturity effects. It is found that startup age (years of operation pre-acceleration) negatively affects funding probability, while accelerator age (program years in operation) positively affected it, aligning with findings from Cohen et al. (2019) and Hochberg, (2016) respectively. It is also observed that having prior funding significantly boosts follow-on funding odds, aligning with the signal-based mechanisms emphasized by Hallen et al. (2023).

The results related to Funding Amount are more complex. Although coefficients for industry-specific programs and those offering corporate access are both positive, aligning with the resource-based argument by Kohler, (2016), Kanbach & Stubner, (2016) and Miller & Stacey (2014), contrary to expectations, the interaction between corporate access and industry specificity was negative and statistically insignificant (or marginally significant in the full model). Practically, startups from accelerators that were both corporate-partnered and narrowly industry-focused tended to raise less total funding than expected. This challenges the common assumption in the literature that more tailored or "elite" programs always yield better results (Hallen et al., 2020; Drori & Wright, 2018). These findings point to potential trade-offs, while corporate access provides downstream investment channels and sector-specific programs enhance domain fit, their combination may constrain startups by reducing their agility or imposing strategic conformity (Sydow et al., 2009). One explanation, in line with Seitz et al. (2024), is that such integrated corporate accelerators help startups go to market faster but may hinder their ability to attract follow-on financing. One interpretation through RBV might be that over-specialization may reduce the

transferability of gained knowledge or networks. These findings thus moderate prior claims and emphasize that over-engineering an accelerator's design may inadvertently reduce its participants' investor appeal. Also, these findings refine existing work by Pauwels et al. (2016) and Winston Smith & Hannigan (2015), who highlight the benefits of specialization and industry alignment but do not account for potential trade-offs when such features overlap. This nuanced result goes beyond prior work by quantifying the interaction effect – an added value of this study is highlighting that more is not always better when it comes to piling on accelerator features and alignment between program design and startup needs is a major key.

The combination of equity funding and training is not directly supported, as the interaction between equity funding and training was dropped due to multicollinearity. However, the full model reveals strong individual effects of equity funding and training, both positively and significantly associated with higher funding totals. These findings align with theoretical expectations from the resource-based view (Barney, 1991), which positions capital equity and knowledge transfer as complementary inputs in a startup's value creation process (Gonzalez-Uribe & Leatherbee, 2018; Cohen et al., 2019). Together, these findings lend credence to the idea that providing “smart capital” - financial capital coupled with intensive support - is a key driver of accelerator success (Hallen et al., 2020; Winston Smith & Hannigan, 2015; Bliemel et al., 2018). From the RBV lens, these elements represent strategic bundles of tangible (capital) and intangible (knowledge, mentoring) resources that are both valuable and imperfectly imitable - key attributes of sustainable advantage. The added contribution here is the clarification that while these elements are impactful, their joint contribution is difficult to isolate without introducing collinearity - an insight with methodological as well as substantive implications.

Overall, this study contributes by decoupling mechanisms often bundled in previous research and showing that not all combinations are additive. Different accelerator features can drive different outcome dimensions, and there may be unintended consequences when combining certain features. This has strategic implications for accelerator design and helps qualify general assumptions found in previous accelerator typologies.

Beyond whether and how much funding startups raise, this study examines how quickly startups obtained follow-on funding after graduation. The initial prediction that corporate access and industry specificity would delay post-acceleration funding due to the complexity is not supported. However, the findings indicate a marginally significant acceleration instead, suggesting that these features may streamline the funding process rather than hinder it. Accelerators that are both industry-specialized and have corporate partners likely provide a very targeted ecosystem for startups, effectively plugging the venture into an “instant network” of sector-specific mentors, customers, and often a dedicated corporate venture arm or investor base. This contradicts the

initial economic reasoning but is interpretable through theory lens. The presence of both characteristics may also create fast-track pipelines to well-identified sources of capital, streamlining the matchmaking process and reducing due diligence efforts. The observed acceleration implies that highly tailored programs, contrary to initial assumptions, may benefit from pre-aligned investor pools. It speaks to the importance of not oversimplifying the effects of focus: while broad programs cast wide nets, focused programs can create rapid pipelines within their niche.

Moreover, the interaction between Strategic Partnership and Non-Equity Funding shows that such combinations reduce the time to follow-on funding. The economic logic here is clear, as non-dilutive funding structures reduce founder friction and dependency, while strategic partnerships provide structured commercialization paths and pre-validated demand. This lowers transaction costs and reduces the search time for complementary investors. The result confirms prior findings that resource-enabling programs lead to earlier traction (Kim & Wagman, 2014) but extends the literature by showing how program architecture shapes temporal outcomes, not just binary success. It also reflects the RBV's emphasis on resource mobilization efficiency, where value is not only in resource possession but also in the speed and ease of deploying it.

Last but not least, the control variables in the time-to-funding models provide additional context that connects to broader theory. It is found that startups with more years of operation prior to acceleration raised funding faster after the program, and those with prior funding took longer to raise the next round. The former suggests that slightly more mature startups have the experience or traction to capitalize quickly on accelerator mentorship, leading to a faster close of financing. The latter finding may at first seem counterintuitive, but it aligns with practical investment dynamics (Browne et al., 2024).

All findings are consistent with the general notion that accelerators “speed up” venture development (Hallen et al., 2020; Winston Smith & Hannigan, 2015). But this study extends that literature by identifying which program features contribute to this speed. Its value-added contribution lies in demonstrating that time-to-funding - an often overlooked dimension - is highly sensitive to accelerator characteristics and their interactions, with strategic and contractual choices playing a decisive role.

Lastly, it is important to note that the shifts in correlations between models indicate that accelerator characteristics do not operate in isolation, and their apparent effects may be influenced, suppressed, or exaggerated depending on the presence or absence of other variables in the model. Therefore, when drawing conclusions, it is important to consider not just whether a variable is statistically significant in one model, but how robust and stable its effect is across multiple specifications. Thus, conclusions should be based on patterns observed across models, not single coefficients, and should be

framed in terms of conditional effects and resource configurations rather than universal truths.

6.1.2. Additional Value

This study makes several significant contributions to the understanding of startup accelerators, advancing both theoretical frameworks and practical insights. Primarily, it offers a nuanced understanding of how heterogeneity in accelerator design influences startup financing outcomes, addressing gaps in existing literature that often treat accelerator features in isolation. First, prior studies often examine accelerator features independently – i.e. these studies (Kohler, 2016; Kanbach & Stubner, 2016; Seitz et al., 2024) focus on corporate accelerators. This thesis innovates by employing interaction terms to uncover conditional effects. The findings support the call by Pauwels et al. (2016) and Cohen et al. (2019) to examine accelerator design elements in combination. This methodological contribution enriches understanding of how program elements co-function rather than operate in isolation. Additionally, it incorporates a three-dimensional approach, as most literature tends to focus either on funding occurrence or total amount raised. By incorporating speed as a third dimension, this research aligns more closely with practitioner concerns and real-world investor dynamics, thus offering a more comprehensive performance perspective. Prior empirical work has often focused on only one outcome at a time – e.g., likelihood of raising VC (Winston Smith & Hannigan, 2015), total capital raised (Hallen et al., 2020), or time to financing (Gonzalez-Uribe & Leatherbee, 2018). By analyzing all three, it is shown that accelerator features can affect these outcomes differently. All these, while based on academic literature and theory, these results are contributing to both literature and industry.

Furthermore, the results illustrate that accelerator characteristics influence not just firm-level capabilities but also downstream financial performance, thereby extending RBV's application from internal firm resources to the design of intermediary institutions. This thesis contributes to the application of the Resource-Based View (RBV) in entrepreneurial ecosystems by demonstrating that the effectiveness of accelerator-provided resources is not universal but rather context-dependent, and yields positive outcomes only when combined appropriately, emphasizing the importance of interactions and complementarities. Thus, this thesis contributes to RBV by offering a contingency-based understanding of how specific resource bundles within accelerator programs differentially shape startups' access to capital and competitive positioning in early markets.

6.2. Limitations & Future Research

6.2.1. Limitations

Every empirical study has its limitations, and it is important to acknowledge these constraints in order to contextualize the findings. The limitations may affect the interpretation of results and the generalizability of conclusions beyond the immediate study context.

Firstly, a methodological limitation concerns the multicollinearity among independent variables and the omission of relevant variables. Despite efforts to include key control variables, the possibility of omitted variable bias remains. In addition, while care was taken to collect reliable information on accelerator characteristics and funding outcomes, several data limitations persist. Funding success was defined as publicly known or recorded rounds, which may underreport informal or undisclosed investments (e.g., angel investments, convertible notes, or revenue-based funding). Some program-specific characteristics—such as the quality of training, strength of alumni networks, or founder satisfaction—could not be quantified and were excluded from the models. These qualitative aspects may have substantial explanatory power but remain unaccounted for. To effectively capture them, a multifaceted approach that combines qualitative and quantitative methods is essential. Instruments such as interviews, questionnaires, and surveys could be employed to assess qualitative dimensions. As qualitative factors could not be calculated and were not captured in the models, their omission could bias the estimated effects of accelerator participation. This challenge of endogeneity – distinguishing the accelerator’s impact from pre-existing qualities of the startups – is a common concern in accelerator research (Seitz et al., 2024).

One other key limitation of the study lies in the sensitivity of coefficient estimates across different model specifications, particularly in the analyses of funding amount and funding speed. In both cases, the inclusion of additional variables and interaction terms in the full models resulted in substantial shifts in the magnitude, direction, or significance of several key predictors. These changes suggest that the effects of individual accelerator characteristics may be highly dependent on the presence or absence of other variables, complicating efforts to draw clear causal conclusions. Some effects that initially appeared positive in the hypothesized models became insignificant or even negative in the full model, reflecting the influence of confounding relationships, suppression effects, or collinearity among predictors. These limitations highlight the challenges of disentangling complex, interrelated resource configurations in observational datasets and underscore the need for cautious interpretation when assessing the independent effect of individual accelerator features.

Moreover, this study is essentially cross-sectional and single-period in nature, analyzing outcomes at a particular point after accelerator participation. This design limits our ability to observe changes over time and to definitively establish causality. Because post-program funding status is examined at one moment dynamic trajectories cannot fully be captured— such as whether accelerators simply accelerate funding that would have happened later anyway, or whether their effect grows or diminishes over time. The cross-sectional snapshot means unobserved differences that evolve in time or account for longer-term survivorship cannot be controlled. Although there is a small portion of the companies (that could be identified) in the dataset that are closed, to mitigate possible survivorship bias. Additionally, without a pre-accelerator vs post-accelerator longitudinal comparison or an experimental control group of non-accelerated startups, attributing outcomes solely to accelerator intervention is difficult. There is an inherent selection bias: accelerators do not randomly select companies, typically, they choose ventures with certain desirable traits. Thus, any observed success after acceleration could partly reflect selection effects rather than program treatment. Recent rigorous studies address this by comparing accelerated startups to similar rejected applicants (Hallen et al., 2014). This study did not employ such a quasi-experimental setup, and thus its results should be viewed with caution on the question of causality.

One other important limitation of this study concerns the use of proxies to operationalize key theoretical constructions. While these proxies were necessary due to data availability and the need for standardization across diverse accelerator programs, they may not fully capture the depth or quality of the underlying constructs. For instance, variables such as Corporate Access and Strategic Partnership were treated as binary indicators, potentially oversimplifying complex and heterogeneous program features. Similarly, Training was measured via self-reported program characteristics, which may not reflect actual implementation or effectiveness. Furthermore, funding amount and speed of funding serve as observable proxies for startup success but do not account for non-financial outcomes, such as market traction or strategic partnerships. Moreover, through this process, I learned the importance of distinguishing between presence and substance of resources, and the need for richer, multi-dimensional measures in future research. This reflection emphasizes that while proxies enable comparability, they also introduce abstraction, which must be carefully acknowledged when interpreting findings and making theoretical claims.

The dataset underpinning this analysis is confined to startups that participated in accelerators within the South Holland region. The sample for this study (accelerated startups in South Holland) is relatively limited in size, which imposes constraints on the analysis. With a limited number of accelerators and participant startups observed, compared to other major studies, each additional predictor in the regression consumes degrees of freedom. Small sample size also accentuates the influence of any

anomalies in the data. While this study's findings are still informative, one must be careful not to over-generalize from a modest sample of firms.

Moreover, while this regional focus provides valuable insights into the local startup ecosystem, it inherently limits the breadth of the data. This raises considerations for generalizability, as the outcomes observed in South Holland may differ in regions with a weaker venture capital presence or distinct industry cluster dynamics. Prior research emphasizes that local context significantly influences resource access and startup performance (Hallen et al., 2014; Chowdhury & Audretsch, 2024). Moreover, as with many studies on young ventures, data availability posed challenges (Seitz et al., 2024). Startups are often private companies with minimal disclosure requirements, especially early-stage ventures. In sum, the findings should be viewed as most directly applicable to similar contexts (early-stage startups in a developed-region accelerator ecosystem akin to South Holland), and extrapolation beyond those bounds should acknowledge the possibility of divergence.

6.2.2. Future Research Directions

Building on the limitations discussed, this section outlines potential directions for future research. These directions encompass both specific extensions of the current study and broader lines of inquiry aimed at deepening and broadening the understanding of how accelerator characteristics impact startup follow-on funding outcomes.

To examine the qualitative dimensions of accelerator programs, future studies should adopt a mixed-methods approach, integrating quantitative analysis with qualitative techniques such as interviews, surveys, and case studies. Qualitative research could address questions such as: What specific changes do founders undergo during acceleration? How do mentorship and networking translate into tangible business outcomes? What challenges do startups encounter post-graduation? These insights can enrich quantitative findings by revealing causal pathways and contextual nuances. By embracing methodological pluralism, future research can offer a more comprehensive evaluation of accelerator programs, uncovering not just "whether" they work, but also "how" and "why" they do so in different settings.

Future research should also adopt more robust methodological strategies and leverage expanded datasets. The use of regularized regression techniques (such as LASSO or Ridge) or Bayesian hierarchical models could help manage multicollinearity and improve the stability of estimates in the presence of many correlated predictors. Also, employing longitudinal or panel data designs would allow researchers to model changes over time and establish stronger causal claims, particularly around funding speed. These steps would not only mitigate the current study's limitations but also

generate deeper insight into how accelerators can strategically bundle resources to maximize their impact.

Longitudinal research designs should also be prioritized in future studies. Moving beyond cross-sectional snapshots, longitudinal studies can track startup performance over time. Following startups across multiple years and incorporating control groups would enable stronger causal inferences and a clearer understanding of long-term outcomes, not only in terms of immediate funding, but also metrics such as revenue growth, profitability, job creation, subsequent funding rounds, and survival or exit events. Such designs would help determine whether accelerators truly change a startup's trajectory or merely accelerate outcomes that would have occurred regardless. They could also answer sustainability-related questions, such as whether accelerator-induced advantages (e.g., quicker funding) persist over time or whether non-accelerated startups eventually catch up.

To improve the generalizability of findings, it is important to replicate similar analytical framework across different regions and ecosystems, both within and beyond the Netherlands. Comparative analyses can distinguish between context-specific and generalizable effects. Over time, a meta-analytic synthesis of regional studies could offer stronger theoretical insights into which accelerator characteristics are universally beneficial and which are contingent on local ecosystem dynamics. Beyond geographic replication, future research can compare different types of innovation ecosystems, contrasting, for example, accelerators in mature, well-funded environments (such as London or Silicon Valley) with those in emerging or resource-constrained ecosystems (such as cities in developing countries or rural areas).

Furthermore, future research should incorporate data on founders and founding teams of startups. Fundraising success is likely shaped not only by accelerator participation but also by the human and social capital of the entrepreneurs involved. Founder-level data can enable exploration of interaction effects, for instance, whether less experienced founders benefit more from accelerators, while serial entrepreneurs gain comparatively less. Understanding such heterogeneity can refine theoretical models and provide practical insights regarding which entrepreneurs are most likely to benefit from acceleration. Overall, integrating micro-level data on individuals can make future analyses more robust and offer a more complete picture of accelerator impact.

In conclusion, the limitations of the present study highlight several promising avenues for further investigation. These future research directions not only address identified gaps but also support practitioners in optimizing accelerator programs and enhancing their ability to foster innovation and entrepreneurial success. Each additional study will contribute to the growing body of knowledge on how accelerators operate within the broader startup ecosystem, ultimately helping to answer unresolved questions and refine best practices for nurturing the next generation of ventures.

6.3. Alignment with MoT

This research aligns with the objectives and academic orientation of the MSc Management of Technology (MoT) program at TU Delft. It utilizes the analytical and innovative capabilities taught through the Management of Technology program, particularly those developed in the Financial Management and Research Methods courses, which provided the foundation for my understanding of finance and independent research. By investigating the characteristics of startup accelerators and their impact on entrepreneurial funding dynamics, this thesis contributes to a deeper understanding of how technology-driven ventures interact with institutional and financial structures in real-world innovation ecosystems.

The study's focus on accelerator design, funding mechanisms, and strategic support reflects the MoT program's core themes of managing innovation and optimizing technology commercialization processes. It leverages a theoretical framework to interpret how different accelerator characteristics shape startup funding path—an approach that resonates with the program's emphasis on using analytical and conceptual tools to solve practical management challenges in technology-intensive environments. Moreover, this research incorporates data analysis, economic reasoning, and empirical modeling, skills emphasized throughout the MoT curriculum. The insights generated can inform policy-making, entrepreneurial strategy, and innovation ecosystem development, thereby reinforcing the MoT program's mission to develop professionals capable of bridging the gap between technology and business.

6.4. Conclusion

This research aimed to investigate how specific characteristics of accelerator programs influence startups' follow-on financing outcomes, drawing on the Resource-Based View (RBV) as the guiding theoretical framework. By analyzing startups from various accelerators in South Holland through regression models, several insights were obtained regarding the impact of different accelerator attributes on key startup financing metrics.

This study finds that the specific design and features of accelerator programs substantially influence startups' subsequent funding outcomes. The findings show that accelerator characteristics influence funding outcomes in non-linear and context-dependent ways. While individual features may offer limited value in isolation, their interaction with other program elements can significantly shape startup trajectories. The results suggest that bundled, complementary resources are most effective and that certain combinations can either amplify or diminish funding success. These insights provide support for an extended RBV framework, where external resource

environments, like accelerators, play a pivotal role in shaping early-stage venture outcomes.

The analysis revealed that accelerator programs offering non-equity funding significantly increase startups' likelihood of securing follow-on financing, aligning with theoretical expectations. Startups participating in non-equity-based accelerators showed higher odds of securing subsequent funding due to perceived lower risks and greater founder-investor alignment. Additionally, privately funded accelerators that provided corporate access were particularly influential, highlighting a synergistic effect. Private accelerators lacking public-sector legitimacy benefit from partnerships with corporations. Corporate access, therefore, substantially enhances legitimacy and resource availability, crucially impacting investor perceptions and increasing funding likelihood. This aligns with RBV by illustrating how strategic combinations of capital and relational assets can substitute for public legitimacy and unlock funding opportunities.

Regarding the total amount of funding raised post-acceleration, the study uncovered nuanced findings. Accelerators providing extensive corporate access or those designed with an industry-specific focus individually contributed positively, however their combined presence yielded diminishing returns, potentially indicating resource misalignment or overly rigid structures that constrain startup adaptability. Thus, although individually beneficial, the joint presence of these features appeared suboptimal for maximizing funding. Surprisingly, the hypothesized beneficial synergy between equity-based funding and training was not strongly supported, likely reflecting complexities around dilution concerns, incentive misalignments, or operational rigidity. However, accelerators explicitly providing strategic partnerships, training, and equity fundings individually showed positive associations with greater funding amounts in comprehensive model analysis.

These results highlight the importance of well-structured programs that effectively combine financial resources with tangible non-financial support, thus enhancing startup legitimacy and market readiness, ultimately leading to higher post-program funding outcomes. Findings suggest that while some resource bundles may clash, others, particularly those that pair capital provision with capability-building, create strong pathways for financial growth. This contributes to RBV by highlighting how program architecture influences not only access to resources, but also the scalability and deployability of those resources.

Analyzing the time to obtain funding post-acceleration revealed significant effects from certain accelerator features. Notably, accelerators offering a combination of non-equity funding and strategic partnerships substantially reduced the time startups took to secure follow-on funding. This finding aligns with resource-based view that strategic alliances signal credibility and market validation to investors, while non-equity funding

enables rapid negotiations without equity dilution complexities, collectively streamlining and accelerating investment decisions. Interestingly, contrary to expectations, accelerators combining corporate access and industry-specific orientations also shortened funding timelines, suggesting deeper sectoral integration and investor networks rapidly facilitated financing despite initial theoretical predictions of delays. The implication is that specialized industry relationships, complemented by corporate linkages, facilitate quicker investor trust and commitment, thus expediting fundraising processes.

These results also contribute to the RBV by introducing speed as a temporal dimension of resource effectiveness, reinforcing the idea that competitive advantage depends not only on the resources startups acquire, but also on how quickly and efficiently they are able to mobilize them.

Practically, these findings offer important implications for three key stakeholders—startup founders, accelerator managers, and investors—by linking the strategic resources examined through the Resource-Based View (RBV) to their distinct objectives. For startup founders, the findings suggest that not all accelerator programs offer the same resource value, founders should strategically select programs that offer non-equity funding or corporate access, as these combinations are associated with higher odds of securing follow-on funding. This aligns with the RBV notion that valuable, rare, and non-substitutable resources, such as deep industry ties or smart capital, can enhance venture competitiveness. For accelerator managers, the results stress the importance of intentional program design. Simply adding more features does not guarantee effectiveness; instead, managers should focus on creating synergistic combinations of resources, such as pairing equity funding with structured training or embedding strategic partnerships in non-equity settings. Moreover, negative or diminishing interaction effects indicate that resource bundling must be context-aware, rather than additive. Lastly, investors can use these insights to better assess the resource environments startups have been embedded in prior to pitching. Startups graduating from accelerators with meaningful corporate or strategic linkages may possess stronger intangible assets and accelerated capital readiness, signaling lower risk and higher scalability potential. Overall, the study illustrates how understanding the configuration and effectiveness of external resources - not just the startup's internal capabilities - can provide all three stakeholders with a more nuanced, theory-informed basis for decision-making.

In summary, accelerator characteristics critically shape startups' financing outcomes after program completion. However, caution is advised regarding the simultaneous implementation of multiple resource-intensive features, such as corporate access and industry specificity, given their potential to create conflicting constraints. The results reinforce the relevance of the Resource-Based View in entrepreneurial settings and point toward the need for more deliberate, context-aware program design by

accelerator managers. All in all, this thesis underscores the importance of carefully balanced program design in determining startup success, laying the foundation for further exploration in accelerator performance evaluation and design optimization. Future research can build on these insights by incorporating longitudinal designs and richer qualitative measures of resource quality and founder experience.

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APPENDIX

Accelerator Characteristics while considering the whole dataset of 30 programs.

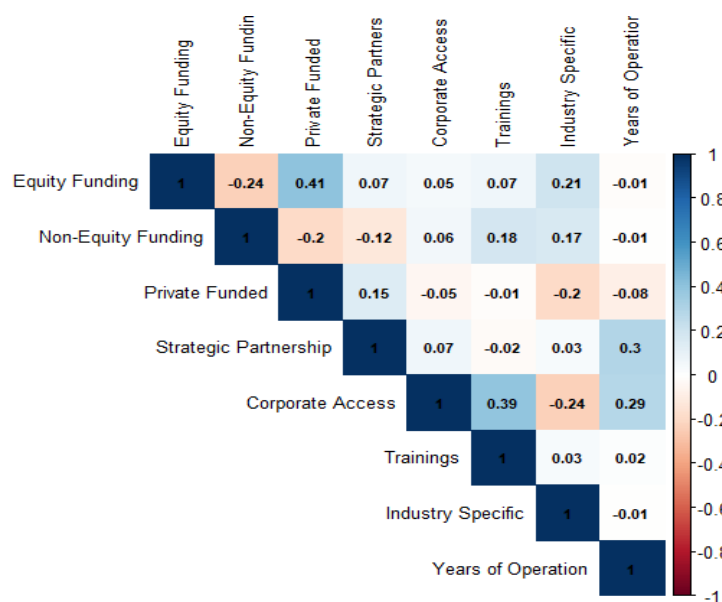
As explained in the main text, the region consists of 30 Accelerator programs, the descriptives for their characteristics for the whole dataset can be found below.

Characteristics \ Descriptives	No. of Obs.	Mean	Median	Std. dev.	Min	Max
Equity Funding	30	0.3	0	0.4661	0	1
Non-Equity Funding	30	0.4	0	0.4983	0	1
Private Funded	30	0.3666	0	0.4901	0	1
Strategic Partnership	30	0.733	1	0.4498	0	1
Corporate Access	30	0.3	0	0.4661	0	1
Trainings	30	0.7333	1	0.4498	0	1
Industry Specific	30	0.4000	0	0.4983	0	1
Years of Operation	30	9.6333	10	4.1646	2	17

All variables are binary, with a value of 1 indicating that the accelerator possesses the given characteristic, and 0 otherwise. The only exception is the last one, which is continuous, measured in Years.

Table 10

These characteristics can be seen in the following phi-coefficient Matrix – also presented in Table 13 form in Appendix below.



Matrix 2

To assess the representativeness of the selected sample of 18 accelerators, independent samples t-tests were conducted comparing their characteristics to those of the full population of 30 accelerators in the region. Across all 8 characteristics tested, no statistically significant differences were found (all p-values > 0.05). While some descriptive differences were noted— a slightly higher presence of equity funding and training in the sample—none reached statistical significance. This suggests that the sample is broadly representative of the full accelerator population, and the analysis based on this subset can be considered valid for drawing generalizable insights about the regional accelerator landscape. Details can be found in the image below.

	Variable	t_statistic	p_value	Sample_Mean	Population_Mean
t...1	Equity Funding	-1.350	0.1862	0.500	0.300
t...2	Non-Equity Funding	0.074	0.9410	0.389	0.400
t...3	Private Funded	-0.150	0.8817	0.389	0.367
t...4	Strategic Partnership	-0.342	0.7344	0.778	0.733
t...5	Corporate Access	-0.979	0.3346	0.444	0.300
t...6	Trainings	-1.388	0.1720	0.889	0.733
t...7	Industry Specific	0.074	0.9410	0.389	0.400
t...8	Years of Operation	-0.274	0.7856	10.000	9.633

Figure 3

Description of Statistics Metrics used in the Thesis

There are several different statistical methods that were used to evaluate the models and are referred to in the text. In the table below, the descriptions of those can be found.

Metric	Description
AIC (Akaike Information Criterion)	Measure used to compare models, balancing goodness-of-fit and complexity. Lower AIC indicates a better model (with fewer unnecessary parameters).
BIC (Bayesian Information Criterion)	Like AIC but with a stronger penalty for model complexity (especially with large datasets). Lower BIC suggests a more parsimonious model.
Deviance	Measures model errors used in logistic regressions (GLMs) and compares the fitted to a perfect model. Lower deviance means better model fit.
McFadden R ²	A pseudo R ² for logistic regression. It compares the log-likelihoods of the null and full models. Higher values indicate better model fit.
Adjusted R ²	A version of R ² that adjusts for the number of predictors in linear regression. Prevents inflation of R ² when adding irrelevant variables.
RSE (Residual Standard Error)	Estimates the standard deviation of the residuals (model errors) in linear regression. Lower RSE indicates that the model's predictions are closer to actual values.

Table 11

Descriptive Statistics of the characteristics of the 18 accelerators used in the analysis.

TABLE 12
Descriptives and correlations among variables¹

Variable	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Launch year	2015	4.67	-													
Equity Funding	0.5	0.51	.1	-												
Non-Equity Funding	0.39	0.5	-.08	-.34	-											
Strategic Partnership	0.78	0.43	-.21	.0	-.12	-										
Corporate Access	0.44	0.51	-.35	-.22	.2	-.06	-									
Working Space	0.4	0.51	-.05	.0	.2	.21	.33	-								
Public Funded	0.61	0.5	.08	-.57*	.17	-.15	.25	.03	-							
Private Funded	0.67	0.49	-.49*	.24	-.4	.19	-.08	-.32	-.56*	-						
Multiple Industries	0.61	0.5	-.05	-.34	-.06	-.15	.25	.03	-.17	.16	-					
University/Research Focus	0.28	0.46	-.03	-.62**	.27	.03	-.06	.19	.49*	-.35	.24	-				
Trainings	0.89	0.32	-.16	-.35	.28	-.19	.32	.32	.44	-.25	.08	.22	-			
Emerging Markets	0.11	0.32	-.23	.0	.08	.19	.04	.04	-.44	.25	-.08	-.22	-.44	-		
International Companies	0.56	0.51	-.2	.22	.25	.06	.35	-.1	-.25	.08	-.03	-.44	.04	.32	-	
Years of Operation	10	4.67	-1.0**	-.1	.08	.21	.35	.05	-.08	.49*	.05	-.03	.16	.23	.2	-
Number of cohorts	7.08	4.72	-.4	-.44	.43	.11	.02	-.06	-.09	-.05	.2	.51	NA	.33	-.09	.4

¹ n = 18 **p < .01; *p < .05.

Descriptive Statistics of the characteristics of the 30 accelerators that were originally in the dataset.

TABLE 13
Descriptives and correlations among variables¹

Variable	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Launch year	2015.37	4.16	-													
Equity Funding	0.3	0.47	.01	-												
Non-Equity Funding	0.4	0.5	.01	-.24	-											
Strategic Partnership	0.73	0.45	-.3	.07	-.12	-										
Corporate Access	0.3	0.47	-.29	.05	.06	.07	-									
Working Space	0.4	0.5	.01	.06	.03	.34	.36	-								
Public Funded	0.63	0.49	-.08	-.41*	.2	-.15	.05	-.08	-							
Private Funded	0.57	0.5	-.27	.28	-.25	.23	.13	-.11	-.67**	-						
Multiple Industries	0.6	0.5	-.01	-.21	-.17	-.03	.24	.11	-.2	.11	-					
University/Research Focus	0.27	0.45	-.07	-.39*	-.03	.02	-.07	-.03	.3	-.23	.34	-				
Trainings	0.73	0.45	-.02	.07	.18	-.02	.39*	.18	.01	.23	-.03	.02	-			
Emerging Markets	0.1	0.31	-.27	.02	.18	.2	.02	-.05	-.21	.29	-.18	-.2	-.05	-		
International Companies	0.53	0.51	-.26	.17	.08	.19	.32	-.05	-.02	-.01	.05	-.19	.19	.31	-	
Years of Operation	9.63	4.16	-1.0**	-.01	-.01	.3	.29	-.01	.08	.27	.01	.07	.02	.27	.26	-
Number of cohorts	7.06	5.23	-.39	-.32	.14	.23	.29	.14	-.1	.09	.31	.36	NA	.25	.16	.39

¹ n = 30 **p < .01; *p < .05.

List of the 18 Accelerator Program's whose Start-Ups are used in the analysis.

Name	Characteristics
Platform Zero	Equity Funding, Private Funded, Strategic Partnership, Working Space, Trainings, Industry Specific, Local
Carbon Removal ClimAccelerator	Equity Funding, Mixed Funded, Strategic Partnership, Corporate Access, Trainings, Industry Specific
NWO Take-off	Non-Equity Funding, Government Funded, Trainings, University/Research Focus, Local
Quantum Delta NL	Equity Funding, Government Funded, Strategic Partnership, Working Space, Trainings, Industry Specific, Local
ClimateLaunchpad	Mixed Funded, Corporate Access, Trainings, Local
TMM Ventures	Equity Funding, Private Funded, Strategic Partnership, Local
World Startup Factory	Equity Funding, Private Funded, Trainings
Unknown Group	Equity Funding, Non-Equity Funding, Private Funded, Strategic Partnership, Corporate Access, Working Space, Trainings
FoodStars	Non-Equity Funding, Government Funded, Strategic Partnership, Trainings, Industry Specific
Truvalu.startups	Equity Funding, Private Funded, Strategic Partnership, Industry Specific, Emerging Markets
Rotterdam Mobility Lab	Non-Equity Funding, Strategic Partnership, Corporate Access, Working Space, Government Funded, University/Research Focus, Trainings
PortXL	Mixed Funded, Strategic Partnership, Corporate Access, Trainings
Rotterdam Internet Valley	Mixed Funded, Strategic Partnership, Working Space, Trainings, University/Research Focus, Local
EIT Health	Equity Funding, Non-Equity Funding, Government Funded, Corporate Access, Working Space, Trainings, Industry Specific
The Justice Accelerator by HiiL	Non-Equity Funding, Private Funded, Strategic Partnership, Corporate Access, Working Space, Trainings, Emerging Markets
WorldStartup	Equity Funding, Private Funded, Strategic Partnership, Trainings
ECE Campus	Government Funded, Strategic Partnership, Corporate Access, Working Space, Trainings, University/Research Focus, Local
LifeSciences@work	Non-Equity Funding, Mixed Funded, Strategic Partnership, Trainings, Industry Specific, University/Research Focus, Local

Table 14

Disclaimer – Use of Generative AI

Throughout the writing process, I utilized generative AI (ChatGPT by OpenAI) as a tool to improve the clarity, coherence, and fluency of my writing. Typical prompts included requests such as "Rewrite this in better English" or "Correct the following sentence" It is important to emphasize that the core ideas, structure, and content of this thesis are solely my own. AI was employed exclusively for language refinement and expression. No AI-generated suggestions were used without my full review and editing, before being incorporated into the final document.