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The accelerator advantage revisited: A closer look at the performance of accelerated start-ups

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Statement of Originality

I, Célina Maria Morad, herewith declare to have written this document and that I am responsible for the content of it. I declare that the text and the work presented in this document are original and that no sources other than those mentioned in the text and its references have been used in creating it.

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Abstract

Given the important role start-ups play in economic development and the explosion of accelerator programs worldwide, this study examines the relationship between accelerator program participation and start-up performance. The various performance outcomes are explored through a detailed analysis of 762 start-ups, which include the likelihood of start-up closure, market exit, funding success, the total funding received, and the number of funding rounds. Propensity score matching and different regression analyses are used in the study to reduce confounding factors and bias and ensure a thorough assessment of the relationships. Contrary to some prevalent assumptions, the obtained results suggest that accelerator participation does not significantly lower start-up closure. Nevertheless, this research establishes evidence of the positive role of accelerators in improving start-ups' odds of achieving a successful market exit and procuring funding, with these start-ups securing a higher total amount of funding. Notably, start-ups supported by accelerators tend to engage in fewer funding rounds, suggesting a more efficient capital-raising strategy due to the positive signal accelerator participation serves to investors.

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1. Introduction

In a rapidly changing global business environment, start-ups have become a critical factor in economic growth, job growth, innovation, and development (Casselman, 2021). Due to their contribution to entrepreneurial ecosystems and aid in economic recovery after crises, start-ups are desirable in the global economy (Aljalahma & Slof, 2022). Moreover, the Covid-19 pandemic has caused a spike in the start-up movement in some countries, with more entrepreneurs starting new ventures (Fitzgibbon, 2021; GEM, 2020; Tai, 2021). However, early-stage start-ups frequently face difficulties and have a low chance of survival. In the first five years of operation, 50 per cent of start-ups fail (Turner & Endres, 2017). These new ventures often possess insufficient resources and capacity for long-term survival, have a lack of managerial expertise and market exposure, lack competitive advantage, and numerous other challenges, which could all contribute to this inability to survive (Chan et al., 2020; Gelderen et al., 2005; Hallen et al., 2014).

To help start-ups identify and overcome these challenges, entrepreneurial support organisations (ESOs) have come into existence to enhance the odds of success for start-ups. These specialised organisations are designed to provide entrepreneurs with the necessary tools and resources to succeed in their efforts. ESOs that have emerged over the past decades with the primary objective of encouraging entrepreneurial activity are incubators, accelerators, science and technology parks, maker spaces, and co-working spaces (Bergman & McMullen, 2022). See Appendix A for a detailed overview of each ESO. Especially the utilisation of accelerator programs as a launching pad for businesses is growing in popularity among entrepreneurs. Worldwide approximately 8000 accelerator programs exist, and more than half of them were founded between 2014 and 2020, indicating the rise in interest in such programs (Aljalahma & Slof, 2022; Davidson, 2021; Ermilina et al., 2021).

Accelerators are short-term or fixed-term programs that support start-ups in developing and launching their businesses. They usually provide small amounts of seed money and co-working space to the start-up teams in exchange for equity stakes. Accelerator programs provide networking, educational, and mentoring opportunities by bringing in peers and mentors. Lastly, the accelerator program will conduct an event where the teams of entrepreneurs can present their ideas to eligible investors to close the program (Cohen et al., 2019; Cohen & Hochberg, 2014; Drori & Wright, 2018; Pauwels et al., 2016).

Accelerator programs have gained significant attention not only from entrepreneurs but also from scholars and politicians (Moritz et al., 2022). The effectiveness of accelerator programs on entrepreneurial ventures has been the subject of numerous studies (Crişan et al., 2021). Some studies indicate a positive relationship between accelerator participation and venture performance (Hallen et al., 2020; Regmi et al., 2015), while others demonstrate negligible changes or even adverse effects on start-up performance (Del Sarto et al., 2020; Gonzalez-Uribe & Leatherbee, 2018; Schwartz, 2013; Yu, 2020). Some studies focus only on the survival of accelerated start-ups (Regmi et al., 2015; Yu, 2020), while others cover performance in terms of growth, customer traction and financial capital (Fehder & Hochberg, 2014; Gonzalez-Uribe & Leatherbee, 2018; Hallen et al., 2020; Winston-Smith & Hannigan, 2015). Although they mark a breakthrough in the literature on accelerators, the majority of earlier research has a qualitative nature, relies on databases from only well-known accelerator programs (e.g., Techstars and Y Combinator), and is country-specific and or sector-specific (Canovas-Saiz et al., 2021; Cohen et al., 2019; Crişan et al., 2021; Del Sarto et al., 2020; Winston-Smith & Hannigan, 2015; Moritz et al., 2022; Yu, 2020).

Therefore, this paper aims to build upon the existing literature by investigating the relationship between accelerator participation and start-up performance, utilising a multi-dimensional conceptual framework. This investigation is drawn on a more nuanced and inclusive dataset and evaluates the impact of accelerator participation based on five different performance outcomes. These outcomes have been chosen to reflect the diverse goals of entrepreneurs and to correspond with specific business strategies while staying within the limits of the obtained data set. The primary research question driving this study is:

What is the relationship between participation in an accelerator program and start-up performance?

To delve deeper into this main research question and provide a comprehensive analysis within the context of the available data, several sub-questions throughout the study are addressed:

1) *Are accelerator-backed start-ups less likely to be closed than non-accelerator-backed start-ups?*

2) *Are accelerated start-ups more prone to market exit through an acquisition or IPO compared to non-accelerated start-ups?*
3) *Are accelerated start-ups more likely to receive funding compared to non-accelerated start-ups?*
4) *Raise accelerated start-ups higher total funding than non-accelerated start-ups?*
5) *Do accelerated start-ups establish more funding rounds than non-accelerated start-ups?*

To address the research questions, a quantitative research approach is used, relying on propensity score matching and different regression models. The analysis is conducted on a data set of 762 observations, including start-ups that have participated in accelerator programs and those that have not. The observational data is sourced from the databases Crunchbase and The Venture Studio Index. The final data set spans a broad range of sectors and countries, and it encompasses start-ups from a diversity of accelerator programs, not solely the well-known ones. The obtained results suggest that while accelerator programs do not significantly lower the chances of business closure, they play a statistically significant role in fostering successful market exits via acquisitions or IPOs. Regarding the financial capital of start-ups, evidence has been found that accelerated start-ups are more likely to be funded and raise more substantial total funding while engaging in fewer funding rounds than non-accelerated start-ups.

This multi-dimensional conceptual framework sets this study apart from previous research, which often focused on single-country, single-sector, or single-accelerator program contexts. Moreover, by adding different performance measures than other studies and employing a methodological approach designed to minimise selection bias, a nuanced understanding of the role of accelerators on start-up performance can be provided. Compared to existing studies such as Hallen et al. (2020), Regmi et al. (2015), and Venâncio and Jorge (2022), this study extends the analysis beyond survival and funding outcomes to include various market exit strategies and the number of funding rounds, thus offering another perspective on accelerator impact. However, the obtained findings should be interpreted in the context of the study's limitations, and further research is needed to confirm and extend these results.

Additionally, given the advantages these programs may have for the entrepreneurial ecosystem and economy, practitioners and policymakers would benefit greatly from understanding the many roles that accelerators play and the effectiveness of such programs (Hallen et al., 2020;

Hawari-Latter et al., 2021). Therefore, the results of this study not only inform the academic debate about the effectiveness of accelerator programs but also hold important implications for policy and practice. From a policy perspective, understanding the impacts of accelerator participation on start-up performance can guide policymakers in formulating supportive policies and programs that foster start-up ecosystems. For entrepreneurs, understanding the potential benefits of accelerator participation can aid in strategic decision-making. For instance, start-ups aiming for successful market exits or seeking more substantial funding could consider participating in accelerator programs. From a managerial standpoint, the results could help those running accelerator programs to refine their offerings. By understanding their impact on different performance metrics, accelerators can better cater to the needs of diverse start-ups. Given the positive relationships found in this study, they might focus on providing resources or mentoring that supports market exits.

The remainder of this paper is structured as follows: Chapter 2 provides the literature review and the established hypotheses. Chapter 3 elaborates on the methodology adopted for this research and the data used. Chapter 4 offers the hypotheses testing and the research results. Chapter 5 discusses the obtained results, and Chapter 6 outlines the limitations and potential directions for further research. Lastly, Chapter 7 concludes the paper.

2. Literature review & hypotheses development

Previous studies and associated literature on accelerator programs can be divided into two streams. One stream focuses on the conceptual descriptions of the accelerator model, and the other stream emphasises the impact of accelerator programs (Crişan et al., 2021; Del Sarto et al., 2020; Gonzalez-Uribe & Leatherbee, 2018; Hausberg & Korreck, 2021; Leitão et al., 2022; Mohammadi & Sakhteh, 2023). Therefore, the following sub-chapters include the literature review divided into those two streams together with the influence of financial factors and illustrate the developed hypotheses.

2.1 The role of accelerator programs

The late 1950s saw the beginning of the incubation model, which focuses primarily on providing workspace, shared facilities, and various business support services for entrepreneurs (Bruneel et al., 2012). Since then, technological developments and the emergence of the digital economy have altered the character of start-ups and the environment in which they operate, particularly by drastically decreasing the costs and time necessary to bring a product or service to market (Pauwels et al., 2016). Therefore, in response to the changing demands of emerging entrepreneurs, accelerators appeared in the early 2000s (Cohen & Hochberg, 2014; Del Sarto et al., 2020). The first accelerator program, Y Combinator, has funded over 450 start-ups with a cumulative valuation of approximately 7.8 billion USD (Cohen, 2013). The number of accelerators increased to over 3000 by 2016 (Hochberg, 2016), and by 2018 they had funded more than 7000 start-ups (Seed-DB, 2018).

An accelerator program is a fixed-term, intensive, and cohort-based program that aims to accelerate the growth and development of early-stage start-ups. It typically provides participating start-ups mentorship, educational resources, networking opportunities, and seed funding in exchange for equity. More specifically, the program usually lasts for a few months, during which participating start-ups receive guidance from experienced mentors, attend workshops and training sessions, and receive valuable feedback on their business ideas. Accelerator programs also offer opportunities for start-ups to pitch their ideas to investors and potential customers at a public pitch event or demo day ending the program (Cohen et al., 2019; Cohen & Hochberg, 2014; Drori & Wright, 2018; Pauwels et al., 2016).

It can be argued that incubators and business angels are like accelerators as the shared main goal is to "accelerate" and fund new businesses. However, accelerators offer a distinctive type of entrepreneurial education and access to networks that aid in overcoming time compression diseconomies, which are difficulties associated with compressing learning into a shortened time frame and resulting in poor performance (Del Sarto et al., 2020; Hallen et al., 2014; Vermeulen & Barkema, 2002). This entrepreneurial capital, which includes market research, concept development, and investor relationship management, combined with the limited duration, differentiates business accelerators from incubators and business angels (Aljalahma & Slof, 2022; Aloulou, 2021; Chen & He, 2021; Cohen & Hochberg, 2014; Gonzalez-Uribe & Leatherbee, 2018; Hallen et al., 2020).

Moreover, these accelerator tools offer a range of resources and support to help start-ups grow and succeed. They offer networking opportunities with investors and other business owners, access to knowledgeable mentors and consultants, and frequent funding or investment options (Stayton & Mangematin, 2019; Wise & Valliere, 2014). Additionally, the structured program and fast-paced environment of an accelerator can help start-ups refine their business strategy and product development process, leading to faster growth and success (Gonzalez-Uribe & Leatherbee, 2018; Hallen et al., 2020).

Findings from this stream of literature generally point to a favourable influence on the success of accelerated start-ups. Therefore, the emerging hypothesis that will be tested in this paper is the following:

H1: Accelerator-backed start-ups are less likely to be closed than non-accelerator-backed start-ups, ceteris paribus.

2.2 The impact of accelerator programs on start-up performance and exit strategy

Accelerator programs have initially been the subject of studies that have measured their treatment effect, but the results of these studies have been very inconsistent. On the one hand, numerous studies have found that accelerator programs positively impact accelerated start-ups (Fehder & Hochberg, 2014; Hallen et al., 2020; Winston Smith et al., 2013). However, other studies discovered more muted or even adverse effects of accelerators on start-up performance (Gonzales-Urive & Leatherbee, 2018; Yu, 2019).

According to Regmi et al. (2015), approximately 23 per cent of accelerated-backed start-ups have a greater survival rate than start-ups that did not participate in an accelerator program in the United States (US). In this research, survival is defined as still operational or having exited by either an acquisition or IPO; therefore, this research did not differentiate between them. Moreover, Hallen et al. (2014) identified that accelerated start-ups reach key milestones, such as further investments and acquisition, earlier in their venture life cycle than non-accelerated start-ups.

Key milestones for nascent ventures, besides still being operational, are being acquired by another firm or establishing an initial public offering (IPO). Therefore, to reach such market exits, a start-up needs to raise additional funding (Lemley & McCreary, 2019). The most recognised early investors are venture capitalists (VCs) and business angels, with accelerator programs emerging in this field as they also provide seed capital for their participants (Block et al., 2018; Cohen et al., 2019). Therefore, to liquidate the investments made, the founders and its investors focus on potential exit strategies. IPOs and acquisitions are two of the most popular exit strategies. On average, an IPO typically occurs around seven years after the venture's launch, while an acquisition is typically completed when the venture is around five years old (Lemley & McCreary, 2019; Pisoni & Onetti, 2018). However, accelerated start-ups may be younger when establishing one of the two exit strategies as they may signal higher quality to investors due to their participation in an accelerator program and, therefore, receive funding earlier in the life cycle of the business (Kim & Wagman, 2014; Spence, 2002).

Winston-Smith and Hannigan (2015) and Winston-Smith et al. (2013) focused on the exit strategies of accelerated start-ups that participated in the US-based TechStars and Y Combinator accelerator programs compared to start-ups that did not. Their studies demonstrate that accelerated start-ups exit through acquisition or failure more quickly than their matched, angel-funded start-ups. Hallen et al. (2020) identified similar results by analysing the impact of top-tier accelerator programs. However, besides identifying the accelerated speed of funds raised by accelerated start-ups, they also found evidence for the exclusivity of this positive effect, as some accelerator programs had insignificant or even adverse effects on start-up performance.

Elaborating on these less positive findings, numerous studies identified a negative relationship between accelerator participation and start-up performance. According to Yu's (2020) analysis, newly established companies accepted into accelerator programs encounter greater challenges in attaining significant development and financial goals. Moreover, Mas-Verdú et al. (2015) concluded that participation in an accelerator program does not ensure the survival of accelerated start-ups. Other business-related characteristics, such as the number of employees and the operating sector of the start-up, need to be in place for an accelerator to impact survival (Canovas-Saiz et al., 2021; Del Sarto et al., 2020). Similarly, Del Sarto et al. (2020) examined four structural factors unique to start-up businesses (number of employees, sector, technology-/non-technology-based, and export activity). They concluded that joining an accelerator program did not affect the business's survival.

According to Wallenius (2018), start-ups that graduated from a US-based accelerator program have, on average, a short-term valuation between 5.5 million and 7 million USD. Due to this valuation, accelerated ventures are typically too small to afford the costs associated with an IPO procedure. However, as stated by Kim and Wagman (2014) and identified by the before mentioned studies, being a part of a well-known accelerator program sends a high-quality signal to potential investors and may speed up further investment rounds. Therefore, given the literature, the emerging hypotheses that will be tested in this paper are:

H2: Accelerated start-ups are more prone to market exit through acquisition or IPO compared to non-accelerated start-ups, ceteris paribus.

2.3 The impact of accelerator programs on start-up funding

The availability of financial capital significantly impacts a start-up's size, growth, and survival (Åstebro & Bernhardt, 2003; Bruderl et al., 1992; Cooper et al., 1994; Pena, 2002). Start-ups with greater financial resources are better equipped to overcome short-term challenges and managerial errors (Park et al., 2002). Additionally, they can obtain superior resources and technologies and start operating on a larger scale (Paradkar et al., 2015). The literature on the pecking theory highlights that asymmetric information costs can increase the cost of external financing; therefore, start-ups prefer to use internal capital first, then debt, and then external equity (Myers & Majluf, 1984). However, as start-ups expand, founders pursue external funding to finance their initiatives early in the business process (Vaznyte & Andries, 2019).

External funding can be obtained through venture capitalists and business angels; however, accelerator programs are also gaining popularity in this position as they offer seed funding to their participants and provide help in the subsequent funding process (Block et al., 2018; Cohen et al., 2019). The help accelerator programs provide has been found to significantly impact the funding of start-ups, both in terms of the amount of external equity funding and the time taken to raise additional capital (Winston-Smith & Hannigan, 2015; Venâncio & Jorge, 2022). Several studies have highlighted the positive effects of accelerator participation on subsequent funding outcomes.

According to the research by Hallen et al. (2020), start-ups that participated in accelerator programs raised more money over a period of 2 to 3 years than those that were almost approved into the programs. The study also showed that accelerators accelerated securing early rounds of outside equity funds. Additionally, Yu (2020) noted that accelerated start-ups typically obtained higher investments on average. This is also stated by Venâncio and Jorge (2022), who found higher external equity ratios for accelerated ventures compared to non-accelerated ventures, specifically during economic downturns.

Moreover, accelerator programs have strict selection procedures, accepting only a limited number of participants (Cohen et al., 2019; Pauwels et al., 2016). By participating in reputable accelerator programs, start-ups can signal their higher quality and potential to external investors. The study by Winston-Smith and Hannigan (2015) supports this, as participation in top accelerators decreases the time taken for follow-up funding rounds. Similarly, Brown et al. (2019) discovered that accelerated start-ups have easier access to funding, indicating the benefits of accelerator involvement in attracting financial resources. These programs also provide ongoing evaluation and connect start-ups with mentors, industry experts, and venture capitalists, enhancing the signalling effect (Canovas-Saiz et al., 2021; Lee et al., 2011). Being a part of a well-known accelerator program sends a high-quality signal to potential investors and may speed up further investment rounds (Kim & Wagman, 2014; Venâncio & Jorge, 2022).

In contrast, non-accelerated start-ups might also have access to networks, but the scope and legitimacy of these networks are less than those offered by accelerators. Non-accelerated start-ups may therefore have a reduced signalling effect. While these start-ups are free to approach external investors directly, the screening abilities of such investors may be constrained due to a lack of information and available time to assess venture quality (Venâncio & Jorge, 2022).

Findings from this body of literature point to a positive impact on the financial capital of start-ups due to accelerator participation. Consequently, the following emergent hypotheses will be examined in this paper:

H3: Ceteris paribus, accelerated start-ups are more likely to be funded than non-accelerated start-ups.

H4: Accelerated start-ups raise higher total funding than non-accelerated start-ups, ceteris paribus.

H5: Accelerated start-ups establish more additional funding rounds than non-accelerated start-ups, ceteris paribus.

3. Methodology

3.1 The data

To analyse the relationship between the performance and the funding of accelerated start-ups compared to non-accelerated start-ups, observational data from the databases Crunchbase and The Venture Studio Index is used. Crunchbase is a commercial database created in 2007 and is acknowledged as a primary source of company data, especially young companies' data (den Besten, 2020; Retterath & Braun, 2020). Thousands of companies submit monthly information to Crunchbase, and over half a million stakeholders revise and update the data with machine learning and artificial intelligence (Dalle et al., 2017). The database Venture Studio Index is a free public information source focussing only on accelerator programs and their participants. Launched in 2022, researchers with experience in venture capital and entrepreneurial ecosystems manually gather data regarding these programs and their accelerated start-ups (Moran, 2022).

The obtained Crunchbase data set includes 2.241.094 observations and 41 variables, and the obtained Venture Studio Index (VST) data set contains 1.836 observations and 15 variables. Not all included variables in the data sets are of interest since the main objective of this paper is to analyse the impact accelerator programs have on the performance and financials of their participants. Based on the literature review and the objective of this paper, a summary is given in Appendix B of the used variables by studies that have investigated start-up performance and funding in the accelerator context, together with their main findings.

Moreover, given the obtained data and the objective of this research, not all variables are measured the same as in the other studies. Some variables in the Crunchbase and VSI data sets are re-coded, calculated and added to the final data set. It is important to note that the Crunchbase data set includes both data on accelerated and non-accelerated start-ups, while the VSI data set only covers accelerated start-ups. However, it is not specified in the Crunchbase data set which observation did and did not participate in an accelerator program. The VSI data set is used to identify this as most of the accelerated start-ups in the VSI data set are included in the Crunchbase data set. Therefore, based on the unique website home page URLs, LinkedIn URLs, and Crunchbase URLs, the overlapping observations from the VSI data set are filtered out from the Crunchbase data set. This resulted in two data sets; one only includes accelerated start-ups and the other only non-accelerated firms.

A variable indicating accelerator participation is added, and the data sets are merged and cleaned. The variable indicating the sector of the businesses has over 1000 unique values. Therefore, this variable is simplified based on the NACE codes. NACE stands for "Nomenclature statistique des activités économiques dans la Communauté européenne", which translates to "Statistical Classification of Economic Activities in the European Community" (Eurostat, 2008). The NACE codes are a standardised system used to categorise economic activities and industries in the European Union (EU) and are intended as an aid for compiling economic statistics and statements (European Commission, n.d.; Eurostat, 2008). The NACE system provides a hierarchical classification system, with level 1 used in this paper. Level 1 consists of 21 sections labelled from A to U and represents the broadest sectors of economic activities (Eurostat, 2008). A complete list of the 21 sections and their descriptions can be found in Appendix C. By using the NACE codes, a variable named "economic_area" is created with 15 unique values.

The variable indicating the operating country of the business is also simplified since it has over 200 unique values. Instead of a variable indicating the country, a variable indicating the continent is created with the levels Africa, Americas, Antarctica, Asia and Europe. After all the alterations and cleaning, the final data set includes 220.750 observations. In this data set, 452 observations are accelerated start-ups and 220.298 are non-accelerated start-ups.

Finally, in Table 1, an overview is given of the used variables for the analyses with their description and variable type.

Variable name	**Variable type**	**Description**
Status	Categorical	Measures if the business is operating, acquired, IPO or closed.
Total_funding_usd	Numerical	Measures the total funding received in USD.
Num_funding_rounds	Integer	Measures the number of funding rounds.

Funded	Binary	Indicated whether a firm is funded, 1 = Yes and 0 = No.
Accelerator_participation	Binary	Measures accelerator participation, 1 = Yes and 0 = No.
Continent	Categorical	Indicates operating continent, given by Africa, Americas, Antarctica, Asia and Europe.
Sector	Categorical	Measures the operating sector, given by the NACE codes.
Employee_count	Categorical	Measures the number of employees, given by the levels: 1-10, 11-50, 51-100, 101-250, 251-500, 501-1.000, 1.001-5.000 and 5.001-10.000.
Age	Numerical	Measures the age of the business.

Table 1: Overview of variables used for the analyses.

3.2 The method

To answer the main research question and corresponding sub-questions, the research regarding the impact of accelerator participation will be split into two separate analyses. One analysis focuses on the performance of start-ups, measured in ‘operating’, ‘failure’, and ‘exit’ using the logistic regression model. Exit indicates that the start-up exited the market with an acquisition or IPO. The other analysis focuses on the financial aspects of accelerated versus non-accelerated start-ups using logistic regression, multiple linear OLS (Ordinary Least Squares) regression, and Poisson regression. Therefore, based on the variable indicating accelerator participation, the data is adequately matched to make the treatment (accelerator-backed) and control groups (non-accelerator-backed) comparable.

3.2.1 Propensity score matching

The final data set shows an imbalance between accelerated and non-accelerated observations, where 99.8 per cent of the data exists of non-accelerated start-ups and 0.2 per cent of accelerated start-ups. This high imbalance can badly affect the regression models since they are constructed to minimise the overall error rate. Therefore, the statistical models will focus more on the prediction accuracy of the majority class, which results in poor accuracy for the minority class (Krawczyk, 2016; Maalouf, 2011)

Therefore, propensity score matching is used to create a matched sample between accelerated and non-accelerated start-ups. Propensity score matching (PSM) is a method used in observational studies to reduce the effects of confounding variables when estimating the treatment effect of an intervention, in this case, accelerator program participation. PSM computes the likelihood, the propensity score, of an observation being in an accelerator program based on the included control variables. After that, the observations of accelerated start-ups are matched to non-accelerated start-ups based on the calculated propensity scores. PSM aims to create a balanced comparison group by matching similar individuals on observed covariates (Abadie & Imbens, 2016; Caliendo & Kopeinig, 2008).

In this paper, the coarsened exact matching (CEM) approach is used to create pools for the covariate measures on which the sample is matched, resulting in matched accelerator and non-accelerator pairs across the coarsened measures (Iacus et al., 2012). CEM simplifies the data by binning numerical values and grouping together categorical values. This process, known as coarsening, helps to reduce the level of detail in the data, which simplifies the matching process and mitigates the impact of minor differences between units. Subsequently, exact matching is performed to establish comparable treatment and control groups. Treatment units with specific combinations of coarsened covariate values are exclusively matched with control units possessing the same combinations (Blackwell et al., 2009; Greifer, 2022; Iacus et al., 2012).

The chosen covariates on which the sample is matched are age, the number of employees, the sector and the continent. Based on the causal inference theory, variables that (1) influence both accelerator participation and the outcome variable and (2) variables that do not have a direct relationship with the treatment but have a direct relation with the outcome should be included in the propensity score model (Pearl, 1995; Pearl & Mackenzie, 2018; Zhao et al., 2021). Therefore, age, sector, employee count, and continent are relevant variables that may influence accelerator participation, as well as status and financial performance. For example, different age groups may have different entrepreneurial experiences or resources available to them. The sector can affect the business environment and competition, while the employee count reflects the size and maturity of the company. The continent can capture regional differences, such as market conditions and access to resources. Including these covariates will decrease the variance of the outcome estimates without increasing bias (Brookhart et a., 2006; Cuong, 2013). In contrast, the total funding received, for example, is not included as a covariate in the matching process as funding received may be influenced by the treatment itself. Including such a variable can increase bias (Cuong, 2013).

After the coarsened exact matching method, the balance is checked by comparing standardised mean differences (SMDs) (Zhang et al., 2019). With the love plot in Figure 1, the SMD balance is visualised. The love plot compares the SMDs of the included covariates before and after matching. As can be seen, the adjusted SMDs are all within the threshold of 0.1, indicating that balance is achieved (Austin, 2011). Of the 452 accelerated companies, 381 are successfully matched with comparable non-accelerated companies. Therefore, 71 accelerated and 219.917 non-accelerated companies could not be matched. These unmatched companies are excluded from the subsequent analyses, making the final data set consist of 762 observations. Lastly, during the analyses, cluster-robust standard errors are applied to account for the matching weights and the pair membership (Abadie & Spiess, 2022; Austin, 2013; Wan, 2019).

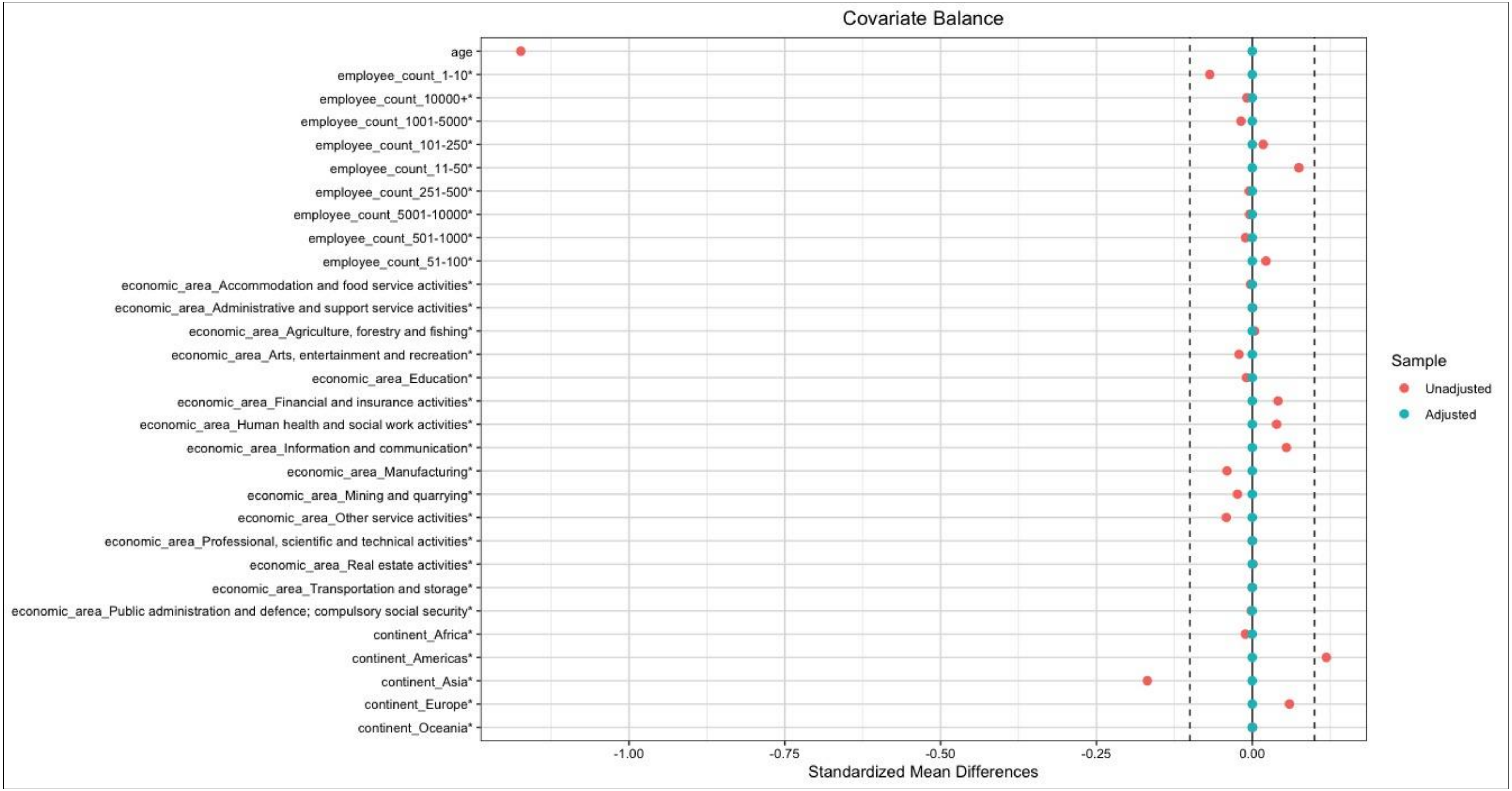

Figure 1: Love plot of the SMDs of the included covariates before and after the PS

3.2.2 Logistic regression

Considering different performance indicators, this study investigates the relationship between accelerator participation and start-up performance. Start-up performance is assessed using two binary outcomes: operating status (operating versus closed) and exit strategy (operating versus exit, including IPO and acquisition). Additionally, the analysis examines the association between accelerator participation and the binary variable measuring being funded or not being funded.

Therefore, the appropriate statistical model to use is the logistic regression model. Logistic regression is a statistical method used to model the probability of a binary dependent variable. It is based on the logistic function, also known as the sigmoid function, which allows estimating the probability of the outcome variable falling into a specific category. (Menard, 2002; Pusztova & Babic, 2020). The dependent variable in the logistic regression model is expected to have a binary distribution, generally represented by 0s and 1s. The objective is to model the relationship between the predictor variables and the likelihood that the outcome would fall into the "success" category (coded as 1) (Sperandei, 2014).

The logistic regression model can be expressed using the logit transformation, which is the natural logarithm of the odds ratio. The logit transformation ensures that the predicted values fall between negative and positive infinity. The logistic regression equation takes the following form:

$$\text{logit}(p) = \beta_0 + \beta_1X_1 + \beta_2X_2 + ... + \beta_pX_p$$

Here, “p” represents the probability of the outcome variable being in the "success" category, given the predictor variables X_1, X_2, ..., X_p. β_0, β_1, β_2, ..., β_p are the estimated coefficients associated with each predictor variable, representing the change in the log-odds of the outcome for a one-unit change in the corresponding predictor variable, assuming all other variables are held constant (DeMaris, 1995; Hensher & Greene, 2003). Therefore, using components of linear regression transformed in the logit scale, logistic regression identifies the most robust linear combination of variables with the most significant probability of detecting the observed outcome (DeMaris, 1995; Kleinbaum et al., 2002; Sperandei, 2014; Stoltzfus, 2011).

Furthermore, logistic regression provides estimates of odds ratios, which quantify the change in the odds of the outcome for a one-unit change in the predictor variable, holding other variables constant. Odds ratios greater than 1 indicate a positive association between the predictor variable and the likelihood of the outcome, while odds ratios less than 1 indicate a negative association. By examining the coefficients, p-values, and odds ratios in the logistic regression model, insights are obtained regarding the direction and strength of the relationship between the predictor variables and the probability of the outcome.

Like other statistical models, the logistic regression model is based on a set of assumptions that need to be tested and met for the model to be valid and reliable. This set of assumptions includes independence between the response and explanatory variables, linearity, independent errors, and no multicollinearity (Peng et al., 2002). The assumptions are assessed and met, resulting in the following logistic regression models per hypotheses:

<u>Hypothesis 1 and 2:</u>

$$logit\ (P_i)status = \log(\frac{P_i}{(1 - P_i)})$$
$$= \beta_0 + \beta_1\text{accelerator\_participation} + \beta_2\text{age} + \beta_3\text{employee\_count} + \beta_4 economic\_area + \beta_5\text{continent} + \beta_6 num\_founding\_rounds + \beta_7 total\_funding\_usd + \beta_8 funded + \varepsilon_i$$

To test hypothesis 1, the outcome variable status focuses only on the category “closed”. By indicating interest in the likelihood of start-ups being in the “closed” category, the relationship between accelerator participation and being closed can be assessed.

For hypothesis 2, the same statistical model will be used. However, the outcome variable focuses only on the exits acquired and IPO compared to the status “operating” while excluding the observations that are within the “closed” category. Therefore, the relationship between accelerator participation and having exited the market by acquisition or IPO can be assessed.

<u>Hypothesis 3:</u>

$$logit\ (P_i)funded = \log(\frac{P_i}{(1 - P_i)})$$
$$= \beta_0 + \beta_1\text{accelerator\_participation} + \beta_2\text{age} + \beta_3\text{employee\_count} + \beta_4 economic\_area + \beta_5\text{continent} + \beta_6 num\_founding\_rounds + \beta_7 total\_funding\_us + \varepsilon_i$$

3.2.3 Multiple linear regression

Multiple linear regression is used to analyse the relationship between accelerator participation and the amount of funding received. Multiple linear regression is an extension of simple linear regression that allows for analysing the relationship between a continuous or numeric dependent variable and two or more independent variables (Uyanık & Güler, 2013).

In multiple linear regression, the goal is to estimate the regression coefficients for each independent variable, representing the change in the dependent variable associated with a one-unit change in the corresponding predictor while holding other predictors constant. Estimating the regression coefficients in multiple linear regression is done using the Ordinary Least Squares (OLS) method. OLS estimates the coefficients by minimising the sum of squared differences between the observed values of the dependent variable and the predicted values based on the regression equation (Montgomery et al., 2021; Weisberg, 2005). The OLS regression assumes that the relationship between the dependent variable and the independent variables is linear and that the errors or residuals of the model are normally distributed and have constant variance. The OLS estimator provides unbiased and efficient estimates of the regression coefficients under the assumptions of linearity, independence, normality, no perfect multicollinearity, no endogeneity, and no heteroscedasticity (Dismuke & Lindrooth, 2006; Montgomery et al., 2021). The assumptions are assessed and met, resulting in the following multiple linear regression model:

Hypothesis 4:

$$\begin{aligned} LogTotal\_funding\_usd_i &= \beta_0 + \beta_1 accelerator\_participation + \beta_2 age + \beta_3 employee\_count \\ &+ \beta_4 economic\_area + \beta_5 continent + \beta_6 funded \\ &+ \beta_7 num\_funding\_rounds + \varepsilon_i \end{aligned}$$

3.2.4 Poisson regression

To analyse the count data representing the number of funding rounds, a Poisson regression is used. This regression model was chosen due to the inherent characteristics of count data, such as non-negativity and discreteness. The primary assumption of Poisson regression is that the mean and variance of the count variable (the number of funding rounds) are equal, a condition known as equidispersion. Overdispersion occurs when the variance value exceeds the value of the mean (Gardner et al., 1995; Hayat & Higgins, 2014).

This equidispersion assumption often does not hold when analysing real-world data, as count data frequently exhibit overdispersion. Overdispersion is a result of several factors, including the presence of a response variable with a higher variance than expected due to unobserved heterogeneity from other variables, the influence of other variables that causes the probability of an event to depend on previous events, the presence of outliers, and the presence of excess zeros in the response variable (Saputro et al., 2021). Alternative models like negative binomial regression or zero-inflated models may be more appropriate in these scenarios. However, when the equidispersion assumption holds, Poisson regression provides a robust and intuitive framework for modelling count outcomes (Bolker, 2017; Coxe et al., 2009; Gardner et al., 1995). Therefore, the presence of overdispersion is statistically tested with the “dispersiontest” function from the AER package in R. The null hypothesis states no overdispersion, and the alternative hypothesis states overdispersion. The obtained results indicate no presence of overdispersion since the alternative hypothesis can be rejected based on the statistically insignificant p-value (0.9996 > 0.05) (Bolker, 2017).

The estimated coefficients in a Poisson regression represent the expected change in the log count of the dependent variable corresponding to a one-unit shift in the respective predictor while holding all else constant (Coxe et al., 2009). Moreover, maximum likelihood estimation techniques are employed to estimate the coefficients in the Poisson regression model. This method provides efficient and unbiased parameter estimates under the assumptions of the model, including equidispersion (Hayat & Higgins, 2014). The estimated coefficients, once exponentiated, represent incidence rate ratios (IRR), which provide interpretable measures of the effect sizes of the predictor variables on the count outcome (Coxe et al., 2009; Miaou, 1994). Therefore, the following statistical model is used:

<u>Hypothesis 5:</u>

$$Num\_funding\_rounds_i = \beta_0 + \beta_1 accelerator\_participation + \beta_2 age + \beta_3 employee\_count + \beta_4 economic\_area + \beta_5 continent + \beta_6 funded + \beta_7 total\_funding\_usd + \varepsilon_i$$

4. Results

With the purpose of testing the hypotheses and providing an overview of the relation between accelerator participation and start-up performance, logistic, linear, and Poisson regression are used. The obtained results are presented with their corresponding hypothesis. All models incorporate the matching weights and account for pair membership using cluster-robust standard errors.

4.1 The relation between accelerator participation and start-up survival

Logistic regression is used to analyse the relationship between accelerator participation and start-up performance, specifically, whether a start-up is closed and thus failed its business. In this logistic regression, the dependent variable measures being closed or not while considering the included independent variables. The obtained coefficient estimate for accelerator participation is given in Table 2, and Appendix D shows the entire model. Table 2 gives an overview of the estimate in log-odds, the odds ratio, and the corresponding p-value.

Variable of interest	**Log-odds**	**Odds ratio**	**P-value**
Accelerator_participationYes	0.080832	1.084189	0.82825

Table 2: Logistic regression coefficient estimate in log-odds and odds ratio for hypothesis 1

As can be deduced by the table above, the main independent variable, accelerator participation, is not statistically significant (p-value = 0.82825 > 0.05). This suggests insufficient evidence to conclude that being accelerator-backed has a meaningful impact on the odds of start-ups being “closed” when considering the other variables in the model. Therefore, the null hypothesis cannot be rejected.

However, it is important to note that the direction of the estimated coefficient is positive (log-odds of 0.080832 and an odds ratio of 1.084189), suggesting that if there were a relation, firms participating in an accelerator would be more likely to close than those not participating.

4.2 The relation between accelerator participation and start-up market exit

Logistic regression is used to analyse the relationship between accelerator participation and start-up market exit. The outcome variable in this logistic regression model measures operating versus market exit. Market exit is indicated by being acquired or having done an IPO. The obtained coefficient estimate for accelerator participation is given in Table 3, and the complete model of estimated coefficients is given in Appendix E.

Variable of interest	**Log-odds**	**Odds ratio**	**P-value**
Accelerator_participationYes	0.56915	1.766761	0.04058

Table 3: Logistic regression coefficient estimate in log-odds and odds ratio for hypothesis 2

The p-value for accelerator participation is 0.04058, which is below the statistical significance level of 0.05. Therefore, hypothesis 2 cannot be rejected.

The coefficient estimate indicates that for accelerated start-ups compared to non-accelerated start-ups, the odds of market exit (i.e., transitioning from being operational to market exit by acquisition or IPO) are 1.766761 times higher, holding all else constant. In other words, the odds of market exit increase by approximately 77 per cent for accelerator-backed start-ups compared to non-accelerator-backed start-ups.

4.3 The relation between accelerator participation and funding

Logistic regression is used to analyse the relationship between accelerator participation and the likelihood of a start-up being funded, while controlling for the other included independent variables in the statistical model. The outcome variable measures whether a start-up has been funded, and the obtained coefficient estimate measures in log-odds and the odds ratio are given in Table 4 with the corresponding p-value. In Appendix F, the full model can be viewed.

Variable of interest	**Log-odds**	**Odds ratio**	**P-value**
Accelerator_participationYes	1.008493	2.741467	4.738e-05

Table 4: Logistic regression coefficient estimate in log-odds and odds ratio for hypothesis 3

The associated p-value for the estimated coefficient is 4.738e-05, which is significantly smaller than the significance level of 0.05. This indicates strong statistical evidence against the null hypothesis; therefore, hypothesis 3 cannot be rejected.

The estimated odds ratio for "Accelerator_participationYes" is 2.741467. This implies that, holding all else constant, start-ups that participated in an accelerator program have 2.741467 times higher odds of being funded than start-ups without accelerator participation. In other words, the odds of funding are about 2.74 times greater for accelerator-backed start-ups.

4.4 The relation between accelerator participation and the funding size

The multiple linear regression model is used to analyse the relationship between accelerator participation and the amount of funding raised. In Table 5, the coefficient estimate is given with its p-value and the complete estimated model is given in Appendix G.

Variable of interest	**Estimate**	**P-value**
Accelerator_participationYes	0.777976	1.328e-10

Table 5: Multiple linear regression coefficient estimate for hypothesis 4

The p-value of the independent variable measuring accelerator participation is statistically significant at the 0.05 significance level. Therefore, hypothesis 4 cannot be rejected.

The statistical model used provides a log-level regression, implying that the accelerated start-ups have approximately 78 per cent higher total funding amount than non-accelerated start-ups, holding all else constant.

4.5 The relation between accelerator participation and the number of funding rounds

The Poisson regression is used to assess the relationship between accelerator participation and the number of established funding rounds. Table 6 provides the obtained coefficient estimate together with the incidence rate ratio (IRR) and the corresponding p-value. In Appendix H, all coefficient estimates can be found.

Variable of interest	Estimate	IRR	P-value
Accelerator_participationYes	-0.095739	0.908701	0.055817

Table 6: Poisson regression coefficient estimate in the logarithm and IRR for hypothesis 5

The p-value of 0.055817 is slightly higher than the statistical significance level of 0.05 but can be concluded as significant at the significance level of 0.10. Since the obtained result contradicts hypothesis 5, which suggests more funding rounds for accelerated start-ups, while the estimate indicates fewer funding rounds for these start-ups, the alternative hypothesis can be rejected.

The obtained log estimate suggests that the logarithm of the expected count of additional funding rounds for accelerator-backed start-ups is approximately 0.0957 units lower than that of non-accelerator-backed start-ups, ceteris paribus. Given the IRR, accelerated start-ups, compared to non-accelerated start-ups, have a rate of approximately 0.9087 times lower for the number of funding rounds, holding all else constant. Alternatively, in other words, on average, accelerated start-ups have a 9.13 per cent (1-0.908701*100) lower rate of additional funding rounds compared to non-accelerated start-ups, ceteris paribus.

5. Discussion

The main objective of this study is to understand the relationship between accelerator participation and start-up performance, focusing on various outcome variables like the likelihood of start-up closure, market exit, and funding, as well as the total funding received and the number of funding rounds established. Therefore, this study was guided by five research questions. The related hypotheses were tested using different regression models, each providing valuable insights into the role of accelerators in start-up performance.

The first hypothesis suggested that accelerator-backed start-ups are less likely to be closed than non-accelerator-backed start-ups. Contrary to the expectation, the obtained results did not support this claim statistically. This counters the findings by Fehder and Hochberg (2014), Hallen et al. (2020), Regmi et al. (2015), and Winston Smith et al. (2013). These studies highlight that accelerator programs contribute significantly to the survival of start-ups. The identified relationship from this research indicates that accelerated start-ups are more likely to be "closed" compared to "operational" than non-accelerated start-ups. This is in line with the findings of Gonzales-Urive and Leatherbee (2018), Hallen et al. (2020), Mas-Verdú et al. (2015), Winston-Smith and Hannigan (2015), and Yu (2020). Based on the intense mentorship and feedback provided during accelerator programs, Winston-Smith and Hannigan (2015) and Yu (2020) explain that entrepreneurs of accelerated start-ups are better equipped to make exit decisions sooner as the uncertainty over the viability of the business idea is resolved faster. On the other hand, non-accelerator enterprises operating within the same timeframe may continue to operate under unresolved uncertainties due to the lack of intensive mentorship, prolonging their decision-making process regarding viability. However, the relation shows to be insignificant in this research, meaning there is insufficient evidence to conclude a significant relationship between accelerator participation and start-up performance, measured by closed versus not being closed.

The second hypothesis is supported by the obtained result: accelerator-backed start-ups are more prone to market exit through an acquisition or IPO than non-accelerated start-ups. This aligns with the findings of Winston-Smith and Hannigan (2015) and Winston-Smith et al. (2013), who focused only on well-known accelerator programs and identified positive effects between accelerator membership and market exit. Moreover, the finding of this analysis aligns with the general conception that accelerators prepare start-ups for market competition and increase their visibility and legitimacy to potential acquirers or investors (Hallen et al., 2020; Kim & Wagman, 2014).

The third and fourth hypotheses, suggesting that accelerated start-ups are more likely to secure funding and tend to raise higher total funding, also find support in the conducted analyses. This resonates with the work of Block et al. (2018), Canovas-Saiz et al. (2021), Cohen et al. (2019), Kim and Wagman (2014), Winston Smith and Hannigan (2015), and Venâncio and Jorge (2022) who argue that accelerator programs enhance the investment attractiveness of start-ups. This may be explained by the signalling theory, as participation in a reputable accelerator program sends a strong positive signal to potential investors about the quality of the start-up (Hallen et al., 2020; Kim & Wagman, 2014; Spence, 2002).

Finally, addressing the fifth hypothesis, the results showed a statistically significant relationship between accelerator participation and the number of funding rounds. Contrary to the initial expectation, the results indicate that accelerated start-ups establish fewer additional funding rounds than non-accelerated start-ups. This can be explained by the findings of Hallen et al. (2020), Venâncio and Jorge (2022), Winston-Smith and Hannigan (2015), and Yu (2020). These papers highlight that accelerated start-ups not only have a higher average funding size but also obtain funding faster than non-accelerated start-ups. According to Winston-Smith and Hannigan (2015), accelerated start-ups typically secure their first funding round earlier and receive higher funding amounts, thus potentially reducing the need for further funding rounds. They theorise that accelerator participation serves as a signal of quality to investors and that the "demo day" ending the accelerator program forces investors to make quick decisions on the investment opportunity.

6. Limitations and future research

This study provides insightful findings concerning the relationship between accelerator participation and start-up performance. Nonetheless, it is essential to consider the limitations that frame the interpretation of the results and provide a path for future research opportunities.

First and foremost, the sample size of this study was relatively small, with 762 observations. While robust enough to generate some statistically significant results, this sample size may not capture the entire scope and diversity of the start-up and accelerator ecosystem. This could limit the generalizability of the findings. In particular, the chances of type II errors (failing to detect a real effect) increase with smaller sample sizes. Future research would benefit from incorporating more extensive and diverse samples to increase the robustness and generalizability of the results.

Secondly, the data covered a wide range of sectors, accelerator programs, and countries. While this broad coverage allows for a more comprehensive overview, it also introduces additional complexity due to the inherent diversity among different sectors and countries. For instance, the role and impact of accelerator programs may vary significantly between sectors or countries with different start-up ecosystem development levels. Future studies may consider narrowing the focus to specific sectors, countries, or continents to provide a more nuanced understanding of the impacts of accelerator participation.

Thirdly, although propensity score matching helped to account for potential confounding factors and selection bias, endogeneity and selection bias could still influence the results. The start-ups that participate in accelerator programs might differ from those that do not in ways not captured by the observed variables. Moreover, investors do not make funding decisions randomly, which introduces selection bias in assessing the amount of funding received. A Heckman correction can account for this selection bias, but at least one variable is needed for the exclusion restriction. This should be a variable influencing the likelihood of being funded but not the funding size (van Balen et al., 2019). Furthermore, future research might consider using other econometric techniques, such as instrumental variable regression or difference-in-difference estimations, to control for endogeneity and selection bias. As well as including additional control variables.

Finally, this research did not fully account for certain potentially influential factors, such as the quality and fit of accelerator programs or the start-ups' stage at the time of accelerator entry. These factors might play a significant role in determining the effectiveness of accelerator participation. Future research could investigate these factors more explicitly, possibly through qualitative research methods such as interviews or case studies.

7. Conclusion

The main objective of this study is to investigate the relationship between accelerator participation and start-up performance. This is achieved by analysing a matched sample of 762 start-ups, including accelerated and non-accelerated start-ups, and investigating various aspects of start-up performance, including survival, market exit, funding likelihood, funding size, and the number of funding rounds. The various performance indicators are analysed by the logistic, linear, and Poisson regression models to suit the nature of each outcome variable. Moreover, propensity score matching is used to manage potential confounding factors and to obtain the final matched data set.

Five key research questions are addressed, and mixed results are identified. The first research question aims to understand whether accelerator-backed start-ups are less likely to close than their non-accelerator-backed counterparts. Contrary to expectations, the result suggests no statistically significant evidence to support that accelerator-backed start-ups are less likely to close than non-accelerated start-ups. However, a statistically significant result is obtained regarding the second research question addressing the likelihood of market exit for accelerated start-ups. The result indicates that accelerated start-ups have a higher probability of market exit through acquisition or IPO than non-accelerated start-ups, demonstrating the strategic value of accelerator programs in preparing start-ups for the competitive marketplace.

The third, fourth, and fifth research questions investigate the relationship between accelerator participation and start-up funding. The obtained results indicate that accelerated start-ups are more likely to secure and receive higher total funding, affirming the general conception that accelerator programs enhance a start-up's investment attractiveness. On the topic of funding rounds, the study found that accelerator-backed start-ups have fewer additional funding rounds than their non-accelerator-backed counterparts. This suggests that accelerated start-ups reduce their need for multiple funding rounds due to their enhanced attractiveness and early-stage funding.

The unique contribution of this study lies in its multi-dimensional conceptual framework that enables a more comprehensive analysis. Transcending the typical boundaries of single-country, single-sector, or single-accelerator program studies contributes to a richer understanding of the relationship between accelerator participation and start-up performance. Furthermore, the study also stands out in its use of various performance measures and a methodological approach that reduces selection bias, offering a nuanced perspective that supplements previous research.

Despite the produced insights, the study has several limitations. The small sample size may not represent the broader start-up and accelerator ecosystems, potentially limiting the findings' generalizability. The study also spanned numerous sectors and countries, adding complexity due to varying economic environments and start-up cultures. Potential issues such as endogeneity and selection bias may also influence the results. Moreover, the study did not fully consider the start-ups' stage at the time of accelerator entry or the fit and quality of accelerator programs. Future research could address these limitations by exploring more extensive and diverse samples, focusing on specific sectors or regions, and applying advanced econometric techniques. More detailed exploration of factors such as the quality and fit of accelerator programs and the stage of the start-ups during accelerator participation could provide additional clarity and depth to the research.

In conclusion, the study provides a comprehensive understanding of the impacts of accelerator participation on start-up performance. The findings offer valuable insights for entrepreneurs, investors, and policymakers, emphasising the value of accelerators and highlighting areas for further investigation. Despite the limitations, the research adds depth to the current understanding of start-up accelerators and underlines the need for continued exploration.

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Appendices

Appendix A: Overview of featured ESOs

INCUBATORS	**Definitions:** - “A shared office-space facility that seeks to provide its incubatees…with a strategic, value-adding intervention system (i.e., business incubation) of monitoring and business assistance” Hackett & Dilts (2004b, p. 57) - “Property-based organizations with identifiable administrative centers focused on the mission of business acceleration through knowledge agglomeration and resource sharing” Phan et al. (2005, p. 167) **Early example / Current estimate:** 1959 (Batavia Industrial Center, New York) / 7,000 worldwide **Entrepreneurial stage:** Pre-Venture; Infancy
ACCELERATORS	**Definitions:** - “Fixed-length, focused programs for start-ups that provide some combination of mentorship, financial investment, office space, public attention, and certification” Clough et al. (2019) - “Organizations which provide support for start-ups to accelerate their development through one or more processes: learning, validation, access & growth, and innovation” Crișan et al. (2021, p. 80) - “Organizations that aim to accelerate successful venture creation by providing specific incubation services, focused on education and mentoring, during an intensive program of limited duration” Pauwels et al. (2016, p.13) **Early example / Current estimate:** 2005 (Y Combinator, Cambridge) / 3,000 worldwide **Entrepreneurial stage:** Infancy; Early Growth
SCIENCE PARKS	**Definitions:** - “A property-based initiative which (i) has formal operational links with centers of knowledge creation, such as universities and (public and/or private) research centers, (ii) is designed to encourage the formation and growth of innovative (generally science-based) businesses, and (iii) has a management function which is actively engaged in the transfer of technology and business skills to ‘customer’ organizations” Colombo & Delmastro (2002, p.1107) - “An organization managed by specialized professionals, whose main aim is to increase the wealth of its community by promoting the culture of innovation and the competitiveness of its associated businesses and knowledge-based institutions” Hobbs et al. (2017, p. 958)

	Early example / Current estimate: 1951 (Stanford Industrial Park, Palo Alto) / 400 worldwide **Entrepreneurial stage:** Early Growth; Sustained Growth; Maturity
MAKER SPACES	**Definitions:** - “Shared fabrication facilities where members gain access to a range of manufacturing technologies” Browder et al. (2019, p. 465) - “Community workshops in which members pay dues to access tools and workspace” van Holm (2017, p. 2) - “Communities comprised of members with different levels of experience and motivations, working with technology and ideas materialized into some form of physical representation” Pettersen et al. (2019) **Early example / Current estimate:** 1995 (c-base, Berlin) / 1,400 worldwide **Entrepreneurial stage:** Pre-Venture; Infancy; Early Growth
CO-WORKING SPACES	**Definitions:** - “Low-rent alternative workspaces intended to offer a fun and informal atmosphere” Clayton et al. (2018, p. 111) - “Shared workspaces utilized by different sorts of knowledge professionals, mostly freelancers, working in various degrees of specialization in the vast domain of the knowledge industry” Gandini (2015, p. 194) - “Shared office environments that a heterogeneous group of workers (rather than employees of a single organization or industry) pay to use as their place of work, to engage in social interaction and sometimes collaborate on shared endeavors” Waters-Lynch & Potts (2017, p. 420) **Early example / Current estimate:** 2005 (Hat Factory, San Francisco) / 19,000 worldwide **Entrepreneurial stage:** Pre-Venture; Infancy; Early Growth

Note. Retrieved from “Helping Entrepreneurs Help Themselves: A Review and Relational Research Agenda on Entrepreneurial Support Organizations” by Bergman & McMullen (2022).

Appendix B: Overview of variables of interest and trace in other accelerator studies

Variables of interest	Other studies in the accelerator context
Status	Canovas-Saiz et al. (2021); Del Sarto et al. (2020); Gonzalez-Uribe & Leatherbee (2018); Hallen et al. (2020); Regmi et al. (2015); Winston-Smith & Hannigan (2015); Yu (2020)
Total_funding_usd	Canovas-Saiz et al. (2021); Fehder & Hochberg (2014); Kim & Wagman (2014); Winston-Smith et al. (2013)
Num_funding_rounds	Fehder & Hochberg, (2014); Hallen et al. (2014); Hallen et al. (2020); Kim & Wagman (2014); Winston-Smith & Hannigan (2015)
Country	Brown et al. (2019); Canovas-Saiz et al. (2021); Del Sarto et al. (2020); Hallen et al. (2014)
Sector	Fehder & Hochberg, 2014; Hallen et al. (2014); Mas-Verdú et al. (2015); Yu (2020)
Age	Canovas-Saiz et al. (2021); Del Sarto et al. (2020); Venâncio & Jorge (2022)
Employee_count	Canovas-Saiz et al. (2021); Gonzalez-Uribe & Leatherbee (2018); Hallen et a. (2020); Mas-Verdú et al. (2015)
Main findings	
Brown et al. (2019)	Accelerator programs act as a significant 'brokerage mechanism' for entrepreneurs, providing enhanced networks and connections, but warns that attempts to replicate such programs in the public sector may be challenging within weaker entrepreneurial ecosystems.
Canovas-Saiz et al. (2021)	The portfolio size of accelerators, the survival rates of their start-ups, and the number of employees in accelerator programs positively affect the funding received by the start-ups, with US-based and older accelerators having a higher impact on startup survival rates.
Del Sarto et al. (2020)	Participation in accelerator programs alone does not influence firm survival, but specific factors such as technology-based accelerated firms not exporting and service sector firms with small teams not exporting do experience accelerator impact.

Fehder & Hochberg (2014)	The establishment of accelerators positively impacts regional entrepreneurial ecosystems, leading to increased seed and early-stage financing activity that extends beyond accelerated start-ups to non-accelerated companies as well
Gonzalez-Uribe & Leatherbee (2018)	While basic services such as funding and coworking space alone do not affect new venture performance, when bundled with entrepreneurship schooling can significantly enhance the performance, especially in early-stage businesses, emphasizing the importance of entrepreneurial capital.
Hallen et al. (2020)	Accelerators, while beneficial for venture development through broad, intensive, and paced consultation, show varied efficacy, with some also demonstrating sorting dynamics, suggesting that these early accelerator practices could potentially be replicated for independent entrepreneurs, educational programs, and corporate innovation.
Hallen et al. (2014)	Top accelerators speed up venture development, with accelerator-backed ventures raising venture capital and gaining customer traction faster than non-accelerator new ventures; they also highlight that prior founder experience does not replace the unique form of entrepreneurial learning and networks provided by top accelerators.
Kim & Wagman (2014)	In a start-up accelerator's role of information gathering, the chosen portfolio size is often smaller than the efficient level, and that accelerators may prefer to disclose only positive signals about their portfolio firms while concealing negative ones (partial disclosure), and possibly exiting early from these firms, particularly when the portfolio mainly comprises high-quality ventures.
Mas-Verdú et al. (2015)	Firm survival is influenced by a combination of factors such as business size, sector, and technology, rather than just incubators, implying that incubators alone cannot ensure firm survival.
Regmi et al. (2015)	Start-ups graduating from accelerator programs exhibit approximately 23% higher survival rates than other new businesses.
Venâncio & Jorge (2022)	Accelerated start-ups tend to have higher external equity ratios than non-accelerated start-ups, especially during economic downturns, and raise more funding through philanthropic investors, suggesting that accelerators signal the quality of the venture to external equity investors.

Winston-Smith et al. (2013)	Start-ups participated in top accelerator programs (Y Combinator and Techstars) tend to secure follow-up financing sooner, are more likely to either fail or be acquired, are typically founded by entrepreneurs from elite universities, and show greater founder mobility.
Winston-Smith & Hannigan (2015)	Participation in top accelerator programs speeds up exit through increased likelihood of acquisition or closure, and initially quickens the process of receiving follow-on funding from VC investors, but over the long term, it seems to slow down the timing of follow-on funding from VCs, as compared to start-ups funded by top angel groups.
Yu (2020)	Accelerators provide informative signals to startup founders, leading to earlier and more frequent shutdowns, less fundraising upon closing, and more efficient investments compared to non-accelerator companies, implying that accelerators aid in resolving uncertainty around company quality sooner, enabling founders to make informed funding and exit decisions.

Appendix C: Overview NACE codes at level 1

Section	Title	Description
A	Agriculture, forestry and fishing	Activities related to crop and animal production, forestry, and fishing.
B	Mining and quarrying	Activities involving the extraction of minerals and other natural resources from the earth.
C	Manufacturing	Activities related to the transformation of materials or components into new products through various industrial processes.
D	Electricity, gas, steam and air conditioning supply	Activities related to the generation, transmission, and distribution of electricity, gas, steam, and air conditioning.
E	Water supply; sewerage, waste management and remediation activities	Activities related to water collection, treatment, and distribution, as well as waste management and remediation services.
F	Construction	Activities involved in the construction of buildings and civil engineering projects.
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	Activities related to the sale, purchase, and repair of a wide range of goods, including motor vehicles and motorcycles.
H	Transportation and storage	Activities related to the transportation of goods and passengers, as well as storage and warehousing services.
I	Accommodation and food service activities	Activities related to the provision of accommodation services (e.g., hotels, campsites) and food and beverage services (e.g., restaurants, cafes).
J	Information and communication	Activities related to the provision of information, communication, and technology services, including telecommunications, software development, and publishing.
K	Financial and insurance activities	Activities related to financial intermediation, insurance, and other financial services.

L	Real estate activities	Activities related to buying, selling, renting, and managing real estate properties.
M	Professional, scientific and technical activities	Professional services, such as legal and accounting services, scientific research, and architectural and engineering activities.
N	Administrative and support service activities	Activities related to office administration, business support services, and employment placement agencies.
O	Public administration and defence; compulsory social security	Activities related to public administration, defense, and social security services provided by the government.
P	Education	Activities related to education and training services provided by schools, universities, and other educational institutions.
Q	Human health and social work activities	Activities related to human health services, such as hospitals, medical and dental practices, and social work activities.
R	Arts, entertainment and recreation	Activities related to the arts, entertainment, and recreational services, including theaters, museums, sports facilities, and gambling activities.
S	Other service activities	Includes a variety of miscellaneous service activities not classified elsewhere, such as hairdressing and beauty salons, funeral services, and religious organizations.
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	Activities carried out by households as employers, as well as goods and services produced by households for their own consumption.
U	Activities of extraterritorial organizations and bodies	Activities carried out by international organizations and diplomatic bodies.

Note. Retrieved from Eurostat. (2008). NACE Rev. 2 Statistical classification of economic activities in the European Community. European Commission.

Appendix D: Complete coefficient estimates hypothesis 1

		Closed or not	
Variable	**Log-odds**	**Odds ratio**	**P-value**
Accelerator_participationYes	0.080832	1.084189	0.82825
Age	0.20549	1.228130	1.683e-05
Employee_count1001-5000	-16.791	5.102499e-08	0.99705
Employee_count101-250	-0.74933	0.4726826	0.52147
Employee_count11-50	-0.32537	0.7222603	0.46073
Employee_count251-500	-15.586	1.701903e-07	0.99285
Employee_count501-1000	-15.085	2.810899e-07	0.99658
Employee_count51-100	0.72749	2.069874	0.22070
Economic_areaAdministrative and support service activities	-14.916	3.327804e-07	0.99740
Economic_areaAgriculture, forestry and fishing	1.4559	4.288533	0.25468
economic_areaArts, entertainment and recreation	-16.057	1.062907e-07	0.99721
Economic_areaFinancial and insurance activities	-0.51887	0.5951950	0.66892
Economic_areaHuman health and social work activities	-0.34922	0.7052412	0.68725
Economic_areaInformation and communication	0.048097	1.049272	0.94351
Economic_areaManufacturing	0.23119	1.260097	0.85496
Economic_areaMining and quarrying	-15.312	2.239372e-07	0.99307
Economic_areaOther service activities	-0.21027	0.8103692	0.83688
Economic_areaProfessional, scientific and technical activities	-0.62088	0.5374715	0.70330
Economic_areaReal estate activities	1.4162	4.121578	0.27523
Economic_areaTransportation and storage	1.1127	3.042655	0.22813
ContinentAmericas	16.031	9.168875e+06	0.99536
ContinentAsia	15.328	4.538312e+06	0.99557
ContinentEurope	14.864	2.854452e+06	0.99570
ContinentOceania	16.383	1.302771e+07	0.99526
Num_funding_rounds	-0.36571	0.6937066	0.01106
Funded	-0.29060	0.7478162	0.55804
Total_funding_usd	-1.0910e-09	1	0.78844
Intercept	-18.835	6.610081e-09	0.99455

Appendix E: Complete coefficient estimates hypothesis 2

	Exit or not		
Variable	**Log-odds**	**Odds ratio**	**P-value**
Accelerator_participationYes	0.56915	1.766761	0.04058
Age	0.27277	1.313602	3.55e-08
Employee_count1001-5000	18.855	1.544405e+08	0.99670
Employee_count101-250	0.36334	1.438123	0.59411
Employee_count11-50	0.12770	1.136213	0.77964
Employee_count251-500	1.7611	5.818574	0.04651
Employee_count501-1000	-17.925	1.641385e-08	0.99611
Employee_count51-100	0.53185	1.702082	0.35315
Economic_areaAdministrative and support service activities	-15.375	2.102220e-07	0.99731
Economic_areaAgriculture, forestry and fishing	-15.277	2.319936e-07	0.99366
economic_areaArts, entertainment and recreation	-14.373	5.726788e-07	0.99750
Economic_areaFinancial and insurance activities	-0.080916	0.9222710	0.93750
Economic_areaHuman health and social work activities	1.2280	3.414530	0.14595
Economic_areaInformation and communication	0.44060	1.553634	0.58129
Economic_areaManufacturing	0.28076	1.324142	0.80212
Economic_areaMining and quarrying	1.2824	3.605407	0.25678
Economic_areaOther service activities	-0.31057	0.7330322	0.81295
Economic_areaProfessional, scientific and technical activities	1.2772	3.586734	0.34816
Economic_areaReal estate activities	0.24913	1.282909	0.85082
Economic_areaTransportation and storage	-16.052	1.067944e-07	0.99016
ContinentAmericas	16.906	2.197996e+07	0.99503
ContinentAsia	17.490	3.942850e+07	0.99486
ContinentEurope	17.006	2.430335e+07	0.99500
ContinentOceania	1.2540	3.504334	0.99971
Num_funding_rounds	0.089742	1.093892	0.33138
Funded	0.071216	1.073814	0.89683
Total_funding_usd	-2.2323e-10	1	0.81403
Intercept	-22.530	1.641203e-10	0.99337

Appendix F: Complete coefficient estimates hypothesis 3

	Funded or not		
Variable	**Log-odds**	**Odds ratio**	**P-value**
Accelerator_participationYes	1.008493	2.741467	4.738e-05
Age	0.012038	1.012111	0.7703657
Employee_count1001-5000	17.727049	4.997577e+07	0.9968676
Employee_count101-250	17.549304	4.183750e+07	0.9852749
Employee_count11-50	0.833078	2.300388	0.0011610
Employee_count251-500	0.642584	1.901387	0.4424617
Employee_count501-1000	17.473801	3.879498e+07	0.9961785
Employee_count51-100	2.128318	8.400729	0.0009047
Economic_areaAdministrative and support service activities	16.394175	1.317953e+07	0.9971031
Economic_areaAgriculture, forestry and fishing	0.958783	2.608521	0.4144898
economic_areaArts, entertainment and recreation	-1.394399	0.2479821	0.3647421
Economic_areaFinancial and insurance activities	-0.465310	0.6279404	0.4629485
Economic_areaHuman health and social work activities	-0.323704	0.7234646	0.5605613
Economic_areaInformation and communication	-0.179564	0.8356346	0.7167559
Economic_areaManufacturing	-0.770245	0.4628999	0.3228983
Economic_areaMining and quarrying	0.626861	1.871727	0.5930667
Economic_areaOther service activities	-0.667785	0.5128431	0.3231934
Economic_areaProfessional, scientific and technical activities	-0.550819	0.5764776	0.5659660
Economic_areaReal estate activities	16.329774	1.235750e+07	0.9924435
Economic_areaTransportation and storage	-0.062266	0.9396329	0.9388122
ContinentAmericas	0.382663	1.466184	0.7437765
ContinentAsia	0.222292	1.248936	0.8676490
ContinentEurope	-0.058051	0.9436016	0.9608211
ContinentOceania	17.633955	4.553331e+07	0.9928374
Num_funding_rounds	-0.86441	0.4213017	0.9879
Total_funding_usd	0.0012314	1.001232	0.3576
Intercept	0.463359	1.589404	0.7231789

Appendix G: Complete coefficient estimates hypothesis 4

	Total funding in USD	
Variable	**Estimate**	**P-value**
Accelerator_participationYes	0.777976	1.328e-10
Age	-0.018152	0.3548436
Employee_count1001-5000	0.968175	0.3556433
Employee_count101-250	2.880796	2.2e-16
Employee_count11-50	1.188153	4.213e-16
Employee_count251-500	3.304487	3.126e-12
Employee_count501-1000	2.995672	0.0009516
Employee_count51-100	2.209035	2.2e-16
Economic_areaAdministrative and support service activities	0.193156	0.8537552
Economic_areaAgriculture, forestry and fishing	-0.730900	0.1284863
economic_areaArts, entertainment and recreation	-0.038043	0.9710419
Economic_areaFinancial and insurance activities	0.437095	0.1682508
Economic_areaHuman health and social work activities	0.714184	0.0104575
Economic_areaInformation and communication	-0.033328	0.8917759
Economic_areaManufacturing	-0.207067	0.6254644
Economic_areaMining and quarrying	-0.020861	0.9639151
Economic_areaOther service activities	0.062033	0.8660566
Economic_areaProfessional, scientific and technical activities	-0.184671	0.6932919
Economic_areaReal estate activities	0.540679	0.2616361
Economic_areaTransportation and storage	0.045316	0.9038564
ContinentAmericas	1.585331	0.0165362
ContinentAsia	1.013483	0.1702245
ContinentEurope	1.158218	0.0822910
ContinentOceania	0.729521	0.3662173
Funded	27.994238	2.2e-16
Num_funding_rounds	0.397889	2.2e-16
Intercept	-16.611318	2.2e-16

Appendix H: Complete coefficient estimates hypothesis 5

	Number of funding rounds		
Variable	**Estimate**	**IRR**	**P-value**
Accelerator_participationYes	-0.095739	0.908701	0.055817
Age	0.019467	1.0196582	0.0117512
Employee_count1001-5000	0.023880	1.0241678	0.9585037
Employee_count101-250	0.56417	1.7579856	1.146e-08
Employee_count11-50	0.24898	1.2827109	0.0001711
Employee_count251-500	0.52707	1.6939581	0.0012568
Employee_count501-1000	1.1039	3.0159010	2.439e-05
Employee_count51-100	0.48671	1.6269531	3.272e-08
Economic_areaAdministrative and support service activities	0.40852	1.5045861	0.2688992
Economic_areaAgriculture, forestry and fishing	0.37612	1.4566197	0.0446614
economic_areaArts, entertainment and recreation	-0.46188	0.6301005	0.5188490
Economic_areaFinancial and insurance activities	0.12409	1.1321132	0.3566673
Economic_areaHuman health and social work activities	-0.034275	0.9663062	0.7817173
Economic_areaInformation and communication	0.047191	1.0483224	0.6640946
Economic_areaManufacturing	0.31966	1.3766575	0.0493390
Economic_areaMining and quarrying	0.13760	1.1475181	0.4618595
Economic_areaOther service activities	-0.26601	0.7664316	0.1528375
Economic_areaProfessional, scientific and technical activities	-0.39275	0.6751996	0.0720510
Economic_areaReal estate activities	0.39355	1.4822379	0.0226580
Economic_areaTransportation and storage	0.24898	1.2827220	0.1032766
ContinentAmericas	-0.029591	0.9708430	0.9139909
ContinentAsia	-0.13967	0.8696418	0.6533298
ContinentEurope	-0.10347	0.9017038	0.7080588
ContinentOceania	-0.33384	0.7161717	0.3634220
Funded	0.54192	0.4213017	5.503e-09
Total_funding_usd	5.2107e-10	1.7193012	1.378e-05
Intercept	0.14686	1	0.6360855