Predictors of Funding Success in Early-Stage DACH-based Fintech Startups

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Dissertation written under the supervision of Professor Michael Tröge

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Abstract

The present study identifies factors affecting the ability of early-stage fintech startups in the DACH-region to secure funding subsequent to their initial successful fundraising. The research addresses a gap in the existing literature by focusing on a specific sub-segment of startups rather than being geography and sector agnostic. It uses a mixed-methods approach that combines logistic regression analysis with qualitative validation expert interviews on both investor and investee sides.

The central results show that a shorter time to initial funding improves the likelihood of subsequent fundraising within three years. The initial funding type also impacts future fundraising likelihood, with firms initially funded by accelerators or incubators being less likely to secure subsequent investment. The results also show that the educational background of the CEO of the startup affects the ability to raise subsequent funds. A bachelor's degree or a doctorate is predictive of improved funding success whilst an MBA or master's degree is not. Sector-specific findings suggest that SaaS-focused fintech startups are more likely to secure subsequent funding, whereas those in the crypto sector are less likely; however, the use of ICO financing in the latter biases the results.

The results are useful for both prospective investors and investees. Investors can use the identified factors to improve informed investment decision-making at minimal cost. Founders can leverage these findings to enhance their startup's fundraising ability. While the study contains robust findings, it is limited to its geographic and sector-specific scope. Thus, further research is needed in the field.

Keywords: fintech, startup, investment, funding, venture capital, early-stage

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Abstrato

Este estudo identifica fatores que afetam a capacidade de startups fintech em estágio inicial na região DACH de assegurar financiamento após a captação inicial bem-sucedida. A pesquisa aborda uma lacuna na literatura existente, focando em um subsegmento específico de startups. Utiliza uma abordagem de métodos mistos, combinando análise de regressão logística com entrevistas qualitativas com especialistas tanto do lado dos investidores quanto dos investidos.

As principais conclusões indicam que um tempo mais curto para obter financiamento inicial aumenta a probabilidade de captação subsequente dentro de três anos. O tipo de financiamento inicial também impacta as perspectivas futuras, com empresas financiadas por aceleradoras ou incubadoras sendo menos propensas a assegurar novos investimentos. Além disso, o background educacional do CEO desempenha um papel na capacidade de levantar fundos subsequentes, com diplomas de bacharelado ou doutorado sendo preditivos de maior sucesso, enquanto MBA ou mestrado não tiveram o mesmo efeito. Startups fintech focadas em SaaS são mais propensas a conseguir financiamento subsequente, enquanto aquelas no setor de criptomoedas são menos propensas, devido à preferência por financiamento via ICO.

Essas percepções são úteis para investidores e fundadores. Investidores podem usar os fatores identificados para melhorar a tomada de decisões de investimento. Fundadores podem aproveitar essas descobertas para aumentar a capacidade de captação de recursos. Embora o estudo apresente descobertas robustas, reconhece as limitações relacionadas ao escopo geográfico e específico de setor, destacando a necessidade de mais pesquisas em contextos diversificados.

Palavras-chave: fintech, startup, investimento, financiamento, capital de risco, estágio inicial

Título: Previsores de Sucesso de Financiamento em Startups Fintech de Estágio Inicial Baseadas na Região DACH

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Table of Contents

Table of Figures

Table of Tables

List of Abbreviations

ATM: Automated Teller Machine

AUC: Area Under the Curve

B2B: Business-to-Business

B2C: Business-to-Consumer

CEO: Chief Executive Officer

CVC: Corporate Venture Capital

DACH: Germany, Austria, Switzerland (Deutschsprachige Länder)

FOMO: Fear of Missing Out

GDP: Gross Domestic Product

GFC: Global Financial Crisis

ICO: Initial Coin Offering

MBA: Master of Business Administration

M&A: Mergers and Acquisitions

R&D: Research and Development

SaaS: Software as a Service

SHAP: SHapley Additive exPlanations

TMT: Technology, Media, and Telecom

VC: Venture Capital

1. Introduction and research questions

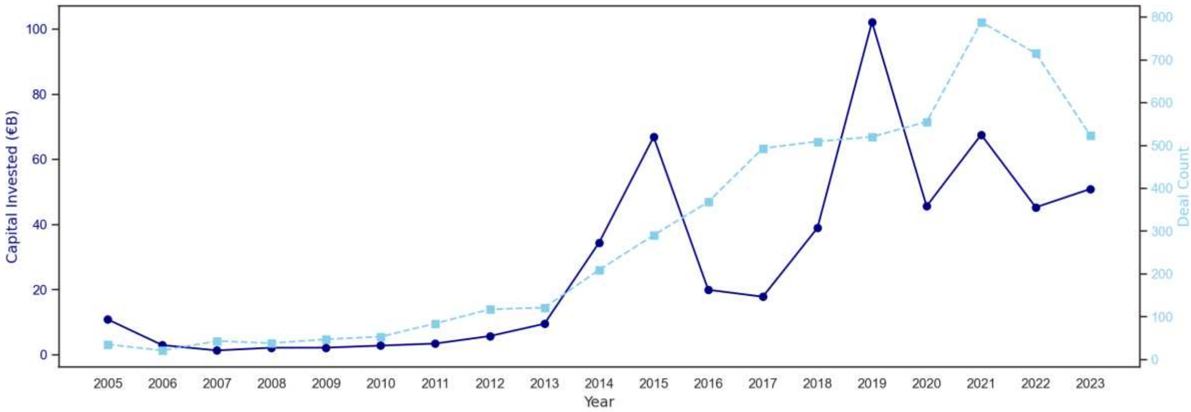
The financial technology sector emerged as a transformative force of the global economy, leaving few facets of legacy financial products and services unaltered. The emergence of the sector was driven not only by pre-existing players in the financial services sector but also new entrants into the market by the form of financial technology (fintech) startups (Treu et al., 2021; Saha and Kansal, 2022).

One of the earliest notable innovations, that was later classified as 'fintech' innovation, was Barclays' first automated teller machine (ATM) in 1967 (Pant, 2020). With the democratization of technologies, new entrants have been increasingly able to compete with legacy financial services providers, creating entire novel sub-segments of the field and leveraging the shortcomings of the old firms (Haddad and Hornuf, 2016). This has led to a boom in the financial technology space with many new entrants in the market. The significant increase in the number of emerging entrants represents a perfect storm of contributing catalysts.

The global financial crisis (GFC) in 2008 swept across the entire financial services industry, weakening trust in legacy service providers and giving way to waves of startups (Haddad and Hornuf, 2016). Thus, elements of the status quo acted as enablers for the novel services and products such as wide-spread internet access, adoption of mobile devices, improved compute power and the advent of advanced data analytics (Laricchia, 2024; Petrosyan, 2023). Fintech firms capitalized on the opportunity to offer more personalized, efficient, and accessible financial services, often targeting underserved or overlooked segments of the market. The total capital invested increased from €44.41B in 2010, directly after the financial crisis, to €279.48B in 2020 and topping out at €424.77B in 2021. Within the same timeframe, the number of deals increased from 878 to 8,336, and topping out at 11,864 (Pitchbook, 2024).

A similar trend of a significant increase in capital investment and the number of deals was also reflected in the DACH-region. In the 2010 to 2020 period capital investment increased from €2.75B with 53 deals to €45.58B with 555, however, peeking in 2019 with €102.15B invested.

Figure 1: Capital invested and number of deals by year in DACH-based fintech companies



Source: Own graphical representation, based on data retrieved from https://my.pitchbook.com/search-results/s415075940/company_chart (Pitchbook, 2024)

In the region, fintech firms are filling innovation gaps where legacy financial institutions are lagging behind. This is often done through alliances between fintech startups and banks which is a unique characteristic of the region. The region has proven to be a successful domain for the financial technology industry with demonstrated by a 20% compound growth rate (von Horn, Hornuf and Kudic, 2021).

However, beyond these factors the geographic scope of the thesis is inspired by the personal experience of a three-month period working at a fintech startup in Germany, during which I was witness of an early-stage fundraising process. Based on this experience it became clear that the access to periodic funding was paramount for the survival and ultimate success of the firm and was viewed as a major milestone by the executive team. On the other hand, investors also search for firms that have the ability to grow and become successful in order to provide a positive return on the investment. One of the key factors influencing how quickly and startups grow is the funding they receive. This financial support allows them to develop their products, hire talented staff, invest in new technologies, and internationalize faster (Davila, Foster and Gupta, 2003; Alfonso et al., 2021). Even though the subsequent funding rounds can result in the dilution of the shares of the investors, the lack of funding for startups is considered as a primary factor when it comes to the reason for their failure (Bednár and Tariskova, 2017). It is thus clear that funding success is a paramount factor in the occurrence of success and the degree of success achieved of startups, including early-stage DACH-based fintech startups.

But what are the factors contributing to the ability for these startups to garner funds? Investors and researchers alike have made significant progress in identifying the contributing factors. However, due to the difficulty of accessing information on investees and costly due diligence processes investigating every prospective investment is not a viable option. Thus, various combinations of accessible data points have been used to attempt to make predictions on startup funding success however, with a focus on early-stage DACH-based fintech startups, no such literature exists. Research is especially sparse when it comes to subsequent funding success. Studying this area is important since it can provide key findings for both prospective investors and investees. The research gap leads us to the overarching 'main' research question of the thesis:

MRQ : *What factors influence the ability of DACH-based early-stage fintech startups to raise funds subsequent to their initial fundraiser ?*

In order to gain a more granular view on topic and to have more accurate guidance on the research, the main research question is supported by further research questions. First, the research uses accessible data from the perspective of prospective investors on the firms and thus we formulate the following research questions:

RQ1: *How do factors emergent in the initial fundraising process impact the subsequent fundraising ability of DACH-based early-stage fintech startups?*

RQ2: *How do publicly available descriptive factors impact the subsequent fundraising ability of the DACH-based early stage fintech startup?*

Second, to gain a temporal view on the effect of these factors on the fundraising of early-stage DACH-based fintech startups, we posit the final research question:

RQ3: *Do different factors influence subsequent fundraising of the DACH-based early stage fintech startups when examining different time windows?*

Note, that due to its ambiguous nature as a success indicator, debt financing is excluded from the study.

In order to answer these questions, the study employs a mixed methods approach. First, a quantitative analysis is conducted by using logistic regression, the findings from which are cross validated by interviews from both the investee and investor side. The quantitative analysis will identify statistically significant predictors, while the qualitative interviews will provide contextual understanding and validate the quantitative findings. This approach is used to improve the robustness of the findings and gain additional context where possible. To facilitate the analysis the following structure is implemented; The literature review examines existing literature on fintech startups, fundraising challenges, and success predictors, at the end of which the hypotheses of the research are established. The study then details the method of analysis including the research design, data sources, and analytical methods used in the study. The subsequent fourth- and fifth-chapters detail and interpret the findings and the implications of the research after which the final two chapters of the thesis (chapters 6 and 7) highlight the limitations and draw concluding remarks.

The thesis aims to present results significant to both prospective investors and the founder or executive teams at fintech startups. For investors, the findings offer insights into making more informed investment decisions with minimal due diligence costs by gaining improved understanding of factors indicative of future fundraising success. For investees, the thesis provides key findings that have an impact on securing funding during early stages of startup development.

The tools used for the completion of the thesis include Stata, Python, and Excel. In accordance with the rules of ESCP Business School, the use of large language models was strictly limited to aiding in formulation, grammatical correction, and translation. However, artificial intelligence tools were not used for original idea or content generation.

2. Literature Review

2.1 The emergence and impact of financial technology startups

This section investigates the pre-existing literature on the emergence and importance on financial technology startups. Where possible, the literature review considers papers focusing on specifics on the German, Austrian and Swiss fintech sectors. However, where a lack of specific published literature is found, literature with less geographic and industry specificity is considered. Note, that the amount of relevant literature specific to the DACH-region is limited.

The wave of technological innovations, referred to as the ‘Fourth Industrial Revolution’, left few facets of the global economy without significant changes (Li, Hou and Wu, 2017). Financial technology driven business models are one of the resulting emergent sectors with the term fintech used as an all-encompassing term for various business models and verticals. These firms offer a multitude of novel services and applications of technology focused around changing and improving traditional financial products and services and introducing completely novel ones (Saha and Kansal, 2022)..

As previously mentioned, a number of diverse sub-segments constitute the fintech sector with financing, payment, and asset management focused products being the largest contributors (Haddad and Hornuf, 2016). Haddad and Hornuf (2016) also argue that many of these firms were a partial or direct consequence of the global financial crisis (GFC) and the subsequent novel banking regulatory regime that arose. Further, the research points out the distrust in legacy financial products and services providers that customer felt post financial crisis was a contributing factor of attractiveness of emergent fintech firms (Haddad and Hornuf, 2016). This finding is also seconded by Cojoianu et al. (2020) observing a statistically significant positive effect between lack of trust in financial incumbents and regional fintech start-up investment. The paper (Haddad and Hornuf, 2016) also points out some key drivers of the formation of fintech startups with predictable results such as the fact that local technology availability and the access to mobile subscription have statistically significant positive effect on the number of startups founded by year and country. However, Van Loo (2018) contrasts this by claiming that the post financial crisis regulatory frameworks can potentially have ambiguous effects on innovation in the fintech realm and has the potential to cause increased market concentration, unfavorably affecting fintech innovation. Thus, it is clear that the global financial crisis acted as a catalyst in the acceleration of the emergence of fintech, but its long-term regulatory effects could impact the market adversely.

When it comes to enablers of fintech innovation, the level of novel technology adoption is high in financial technology startups. This can oftentimes lead to disruption of sub-segments of the financial products and services sector due to the agility of the novel firms (Pant, 2020, Goldstein, Jiang and Karolyi, 2019). Comparing fintech startups and legacy banks, depending on the product portfolio of the latter, the emergence of fintech can be viewed as an existential threat to their business models (Goldstein, Jiang and Karolyi, 2019).

However, the adoption of the emergent technologies, the market share gain and the introduction of completely novel products and services has numerous exogenous effects. Although research is often constrained to local economies, the documented effects of the emergence and adoption of fintech innovations are overwhelmingly positive. Based on the findings of Zuo (2023), the adoption of fintech has a significant positive effect on economic development, however, the effect exhibits heterogeneity across regions. The adoption of fintech is also found to be a key driver for improved financial inclusion especially in high- and middle-income countries where information asymmetries in financial institutions and transaction costs were a major hindrance of decreasing income inequality and reducing poverty (Demir et al., 2020). Further, research (Loko and Yang, 2022) found not only the shrinkage of income inequality caused by the adoption of fintech but that it leads to an increase in the number of women in the workforce and improves the ratio of female employees represented in the workforce. Additionally, the prevalence of financial technology firms on average also improves the financial access of small, female-led firms, and firms with traditionally female skewed hiring practices, however, the positive effects are more prevalent in countries with weaker institutions (Loko and Yang, 2022).

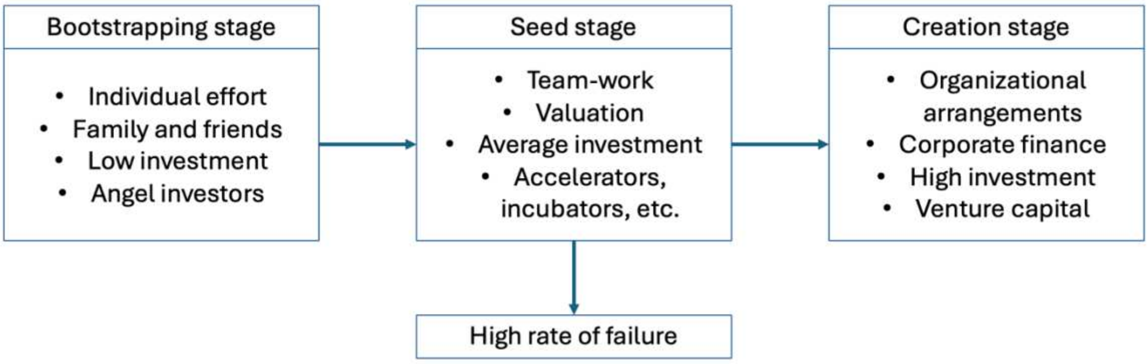
Looking at the resulting sectors at a national level starting with Germany, Dorfleitner et al. (2017) note that while many fintechs are still in an early phase of growth, the sector has shown rapid expansion and potential for significant future growth. The German FinTech market is exceptionally dynamic, with significant growth in financing and asset management sub-segments, suggesting a high potential for future development and success (Gregor Dorfleitner et al., 2017). The Dorfleitner et al. (2017) additionally provide specific estimates when it comes to market perspective estimating significant growth in the FinTech market, with the market volume potentially reaching €148B by 2035 in a real case scenario. Switzerland also boasts a significant domestic fintech sector being the second biggest out the three countries of the DACH acronym, however, its domestic market is not large enough to sustain the sector. This prompts Swiss fintech to internationalize faster than others (Ankenbrand, Dietrich and Rey, 2016). Although the Austrian fintech sector is the smallest, is shows promising development in diverse sectors with payments being the largest and a strong growth rate (Boss et al., 2019).

From a slightly broader DACH-wide perspective, von Horn, Hornuf, and Kudic (2024) investigated the evolution of fintech networks and more specifically the alliances between legacy financial institutions and fintech startups in the region. Fintech startups located in hubs with high geographic density are more likely to collaborate with established banks (von Horn, Hornuf and Kudic, 2021).

2.2 Theoretical underpinnings of startups and financing behavior

In order to understand how startups operate and why they subsequently seek funding we first need to understand the theoretical underpinnings of the stages of development of startups and its consequences. Although there are multiple factors affecting the lifecycle of startups causing significant levels of variance depending on sub-segment, there is an overarching structure to the lifecycle of startups. Salamzadeh and Kawamorita (2015) propose a 'Life Cycle Theory' which includes three distinct stages for startups with their respective operational and investment stages. First, the authors (Salamzadeh and Kawamorita, 2015) describe the first stage of startups life as the 'bootstrapping stage'. The stage is defined as the stage when the initial decision is made to create a profit-oriented project or a business, the initial venture idea is defined, and the initial associated activities are started with the use of personal funds and with the occasional financial support of friends or family members. The 'bootstrapping' label stems from the fact that at this stage of the startup, creative ways of acquiring necessary resources for the early development stage are used without borrowing money. The core purpose of this stage is to demonstrate feasibility of the product, the customer acceptance and managerial capabilities such as cash management capability and team building efforts (Salamzadeh and Kawamorita, 2015). Notably, the authors point out the fact that angel investors are more likely to invest at this stage. The subsequent stage encompassed in the theoretical framework is the seed stage of the startup's lifecycle fueled by initial external financing of limited amounts. The stage is characterized by activities that are oriented towards setting up the business to succeed in the medium-term such as establishing teamwork, prototyping and the initial entry into the commercialization process of the products or services. The researchers (Salamzadeh and Kawamorita, 2015) point out that a significant portion of the ventures fail at this stage even despite the improved financing and support mechanisms available to the startups at this stage such as accelerators and incubators. The subsequent stage is titled the 'creation stage' where the staffing and market entry are prominent enabled by higher amounts of external financing access, which is enabling higher capital intensity activities. This is also the stage where series-level financing is acquired, made possible by the improved track record of the venture. The early-stage lifecycle of the startups can be depicted as follows:

Figure 2: Startup lifecycle theory



Source: Own representation adapted from Salamzadeh and Kawamorita (2015, p.5).

A further important theoretical framework to consider with regards to startup financing and fundraising is the way startups seek and decide on financing options which in its early form was conceptualized as 'Pecking Order Theory'. Newly found ventures compared to established corporations differ in terms of their ability to pledge collateral and thus their financing resources and decisions differ. A major contributor to the theory, Myers (1984) proposes a hierarchy of choice amongst financing options for corporations. Generally, the use of internal financial resources such as retained earnings are preferred due to the lack of information asymmetries, followed by debt and external equity financing. The former of which does not have an adverse selection problem, whereas the latter two do come with a risk premium. However, the literature takes a more nuanced approach.

The view that a firm's value was irrespective of its capital structure proposed by Modigliani and Miller (1958) was later expanded by Myers (1976) arguing that there are multiple factors affecting the borrowing decisions of a firm, such as the availability of internal cash flow (as posited by pecking order theory as the preferential choice for financing new projects), the level of 'tangibility' of the assets of the firm (usually low in the case of early-stage ventures), growth opportunities, and market conditions such as interest rates. We could conclude by saying that there are significant amounts of firm specific attributes contributing to capital structure decisions, thus it is an overgeneralization to claim that the proposed pecking order is followed by firms of all types and sizes.

The proposed theoretical pecking order was empirically investigated by Atherton (2009), finding that indeed there is a difference in financing preferences for new ventures. The findings include a partial support for the proposed pecking order. Startups do not tend to finance themselves using retained earnings and there is no clear preference for debt over equity financing. When financial resources were deemed insufficient, startup founders resorted to alternative bootstrap financing and a wider range of factors affected financing decisions beyond the information asymmetries proposed by pecking order theory. In the cases investigated by Atherton (2009), relational capital and prior experience influenced structures of startup financing, beyond bounded rationality.

2.3 Fundraising in fintech startups

The literature treats the emergence and adoption of fintech as a positive phenomenon unanimously with very few exceptions. However, for its development, survival and ultimately success, fintech startups are in need of financial backing. The primary source of funding for early-stage financial technology firms driving their development stems from equity investment and more specifically venture capital, corporate venture capital (CVC), and angel investor fundings highlighted as some of the most common types (Brown, 2017). Although the literature on early-stage fintech specifics (importance, types, stages, patterns) is limited there are significant commonalities with generalized early-stage venture funding and early-stage tech venture funding (Brown, 2017). Venture capital investments can be divided into stages. Generally, certain stages of startups are associated with specific types of venture capital investment. In the earliest stages startups seek financing from accelerators and incubators, which is followed by pre-seed and seed investments and later with early-stage venture capital investments (Series A and B) and then later stage venture capital investment, however, the investment stages have significant overlaps and the startups do not have to commence with any given stage, this is determined by the stage of development of the business. (Bonini and Capizzi, 2019; Fehder and Hochberg, 2014; Dahiya and Ray, 2011). The funding stages have the following general characteristics (note that they can deviate): In the very early stages of startup development accelerators and incubators can be utilized. Incubators and accelerators offer programs that are a few months long with varying characteristic. They often take an equity stake in exchange for funding, mentorship, networking opportunities, and workshops. The pre-seed round is set for startups beginning their activities with the objectives of initial setup, basic product development, and initial market research. In the seed stage startups focus on developing an innovative product and forming a team. The final rounds concerning the thesis are 'Series A and B' investment stages where in the former the product is developed and in use by an established customer base and in the latter a recurring and stable revenue stream is achieved (Adamiv and Lysa, 2023).

Although not specific to financial technology firms, examining the effect of venture capital funding on the growth rate of startups, it was observed that both the months leading up to the closing of the venture capital investment deal and the months after showed accelerated growth (Davila, Foster and Gupta, 2003). Regarding fintech specific growth acceleration through investment, research (Alfonso et al., 2021) points out the role of regulatory sandboxes and their contribution to increase the proportion of fintechs as a percentage of GDP and significantly increased investment. The previously mentioned positive impact of venture capital funding as opposed to the lack thereof is further highlighted by firm-level (as opposed to macro) outcomes. Although the research does not consider fintech firms explicitly, the sector agnostic finding was made that firms that were able to secure venture capital funding were more likely to internationalize, more likely to formally protect their intellectual property and more likely to engage in innovation (Alfonso et al., 2021). Alfonso et al., (2021) also echoes the previously mentioned more generalized finding that funding in fintechs are driven by venture capital investments and at later stages by M&A activity, although the research also points out that the majority of deals occur in the seed and early stage (>90% in Europe), suggesting that not all ventures are able to gather subsequent funding post early stage fundraiser or that at a given stage venture financing is no longer needed. However, the number of deals closed also varies across time by sub-segment of the fintech market, with the emergence of crypto- and blockchain-focused startups seeing a sharp increase over the 2010-2020 period according to the findings of Alfonso et al. (2021). Along the same logic, Khajehpour, Mahdi and Yousefi Zenouz (2020) find a differential pattern in funding although the primary source of early-stage financing is venture capital investment irrespective of sub-segment. However, the authors find that (predictably) the sub-segment of digital lenders is more reliant on partially financing their operations through debt facilities besides venture capital post first round. When it comes to the ability of fintech startups to raise funds, research also finds that jurisdiction where the firm is based has a significant impact on the ability to raise funds, in particular, fintechs were more likely to gather funding in cases where the difference in the enforcement of financial institution rules was larger between fintech startups and large established institutions. (Cumming and Schwienbacher, 2016).

Besides venture capital funding, fintech startups depending on their objective, products/services also seek equity crowdfunding, with the additional limited examples of receiving public grants, although both represent a small fraction of deals closed and funds raised by fintech startups. With regards to the former, research finds that (although in its current form the limited number and limited volume) crowdfunding has a two-fold beneficial effect, since investors are able to invest in early-stage ventures without having to access former, legacy ways of venture capital investing and startups can raise funds without significant losses of managerial autonomy (Brown et al., 2015) Notably however, the research is not focused on fintechs specifically and considers early-stage startup investments more generally.

It is clear that fintech startups are funded through a multitude of mechanisms with the most prevalent ones being venture capital investments, with the addition of some alternative investment types making up a small fraction of the remaining number of deals. It is also clear that the regulatory environment of the fintechs has some effects on their growth and fundraising ability and that if successful, venture capital funding capital funding has a multitude of positive effects on firm growth and performance, with increased growth even starting pre-closure of the deal. However, the question arises as to how investors of fintech startups make decisions and what expectations are informing and influencing their decision-making process.

According to the research of Hommel and Bican (2020) the motivations of fintech investors are twofold represented by intrinsic and emotional factors. Investors in the field have a significant priority for fintech startups with more than a mere business plan, such as demonstrable prototypes and existing processes. The authors also find that fintech investors are positively biased towards investment opportunities where technology is implemented in manner that is focused on service efficiency and general cost reduction making the business more scalable (Hommel and Bican, 2020). The paper also argues that fintech investors are particularly influenced by the perceived qualities of the management team of the startup. The highlighted qualities include experience and credibility. However, the findings go further arguing that perceived qualities that can have direct implications on the revenue generation potential of the early-stage fintech startup such as the ability to distribute the product are also taken into account (Hommel and Bican, 2020). A further notable claim the authors make is that the perception the management will be able to raise funds subsequent to the investment is also a key decision factor investors take into account (Hommel and Bican, 2020). The findings on the importance of the perceived qualities of the management team were seconded by the non-fintech specific research on venture capital investment decisions by Gompers et al. (2016) arguing that relevant experience and 'founders with clear visions' are imperative in the investment decision-making process and supersede the importance of the actual business model or products offered. The sector agnostic paper by Gompers et al. (2016) also points out the fact that there is lower than expected prevalence of accounting-based and financial metrics-based decision claiming "31% of early-stage VCs reported that they do not forecast cash flows when they make an investment." (Gompers et al., 2016, p. 6).

However, it is not a 'one-way game'. As opposed to the acquisition of funds through grants or equity crowd funding in the case of early-stage startups including fintechs, the role of venture capitalists which as discussed, represent the majority of the number of early-stage deals, is more than just a vehicle for financing and vice-versa a mere investment opportunity. Venture capital investors (both institutional and non-institutional) often act as management advisors and can be deeply involved in the strategic decisions and direction of the startup they invested in which is a significantly time-consuming effort resulting in the limited number of investments VCs can optimally hold (Keuschnigg and Kanniainen, 2004). The importance of investors as advisors is seconded by Kaplan and Strömberg (2001) pointing out the important role of monitoring and advising the startup by the investors not just in an effort to maximize the startups likelihood to succeed but to also mitigate potential principal (investor) – agent (entrepreneur/startup management team) problems from arising.

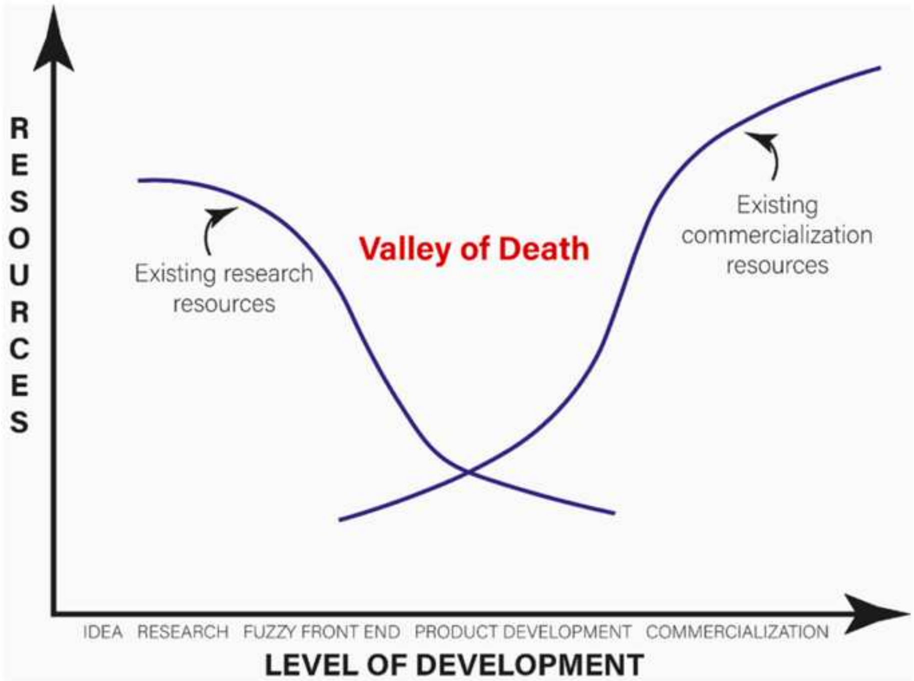
2.4 Consequences of inability to secure funding

Although research on fintech specific literature is very limited, the findings of sector agnostic papers are adaptable. Generally, fintech startups count as innovators in the field which research has shown is more capital intensive than non-highly innovative startups (Brooksbank et al., 2006). The authors (Brooksbank et al., 2006) also argue that a correlation between the innovativeness of the firm and the lack of business experience of the founders exists, which further worsens the chances of fundraising success. However, besides the hindrance of innovation and the adverse severe consequence of lack of fundraising ability is the mass-extinction of early-stage startups. Although literature highlights a multitude of reasons for early-stage startup failure, the lack of ability to secure funding is a unanimously prominent finding (Kreituss, 2016, Ramalakshmi, 2018). More specifically Bednár and Tariskova (2017) found that 66% of early-stage ventures' primary reason for failure was funding related with

34% citing 'lack of money for further development' as the reason, 16% citing 'cost issues' related to cash burn rate, and a further 16% citing 'no investors' as the primary reason in a global sample of startup failures.

The concept of early startup death (with estimates cited at 90% as the industry standard (Ritter and Pedersen, 2022)) is so prevalent that the post initial investment death has received the name of the 'valley of death'. The concept is defined as the period after the initial funds have been raised but the venture does not yet have a self-sustaining revenue stream (Ritter and Pedersen, 2022). The initial funds raised, the cash burn rate of the company, and its subsequent ability to raise funds determine the 'survival' or 'death' of the startup. The depiction below shows a generalized graphical representation of the valley of death with regards to technology driven ventures. However, notably disregarding deviations in funding patterns highlighted by Khajehpour, Mahdi and Yousefi Zenouz (2020) amongst fintech firms:

Figure 3: The valley of (startup) death



Source: Gbadegeshin et al. (2022, p.5)

Although no fintech specific literature exists on successful strategies when it comes to surviving the valley of death, published research details the entrepreneur-focused survey findings for technology driven business models. The authors Gbadegeshin et al. (2022) describe varying strategies in various aspects of the management of the early-stage technology ventures, such as early efforts to generate revenue and pilot the newly developed products, reaping both the benefits of both the financial gains and feedback provided by the customer, whilst more central strategic efforts were commonly centered around increasing the valuation of the company. When it came to internal financial decisions proving to be favorable with regards to survival, startups were conservative with executive salaries and were faster at accepting and generally more accepting of investment offers (Gbadegeshin et al., 2022).

2.5 Predictors of startup (funding) success

Clearly, access to funding is an imperative factor when it comes to the short- and medium-term survival and success of the firm. This sub-chapter of the literature review investigates previous academic works focused on predicting funding success in startups. As opposed to studies where the outcome variable was the sheer survival of the firm or long-term success based on various measures (as will be discussed on the subsequent sub-chapter of the literature review), these studies in particular focus on funding success as the outcome. It is important to note that the literature investigating the aforementioned relationships are neither fintech nor DACH specific. It is also notable that many pieces of published research focused around the predictors set out as a goal to find machine learning models and a combination of independent variables with the highest possible predictive accuracy amongst other measures (AUC, F1, etc.). Although this is different from the objective of this thesis, the resulting (if included in the research) variable importance measures such as SHAP can shed a light on the importance of certain variables when it comes general success/survival prediction and prediction regarding funding success.

Zhyber et al. (2021) used logistic regressions to analyze factors affecting startups' ability to raise funds. Notably, the research was confined to Ukraine and is not specific to financial technology startups but the findings are in line with other studies considering similar factors in other geographies. Closely matched research focused on the DACH-region has not been produced. The variables analyzed by Zhyber et al. (2021) were all binary defined as follows: (1) whether the startup previously managed to garner funding, (2) whether the startup is profit oriented, (3) whether the startup had an active social media presence, (4) whether the business was oriented towards B2B or B2C customers, and (5) whether the startups hold a patent or not. Modeling the data using a logistic regression the authors only found that the variable describing the previous funding of the startup significant with at $0.05<p$ whilst the aforementioned other variables were not, although the second and third were found to be significant at a 10% significance level (Zhyber et al., 2021). However, when implementing interaction terms for the

dummy (binary) variables, the statistical significance of the variables changed. Notably, when interacting the second and fifth and the third and fifth variables, respectively and excluding the third one, all of the variables become significant. In all of the models there is a statistically significant ($p<0.01$) positive relationship between the record of previous funding and subsequent funding success. This is in line with the findings of Ling (2015) suggesting that specifically firms with prior venture capital funding were more likely to receive subsequent funding. The same effect was found by Kleinert, Volkmann and Gruenhagen (2020) where the outcome was in particular measured as a success in subsequent equity crowdfunding, suggesting that for non-institutional investors and institutional investors alike, prior funding is a positive signal as to the qualities and likelihood of success of the startup. The researchers (Zhyber et al., 2021) also found that an active presence on social media when the variable describing the firm's orientation was not added to the model had a statistically significant ($p<0.01$) positive impact on the likelihood that the startup was able to raise funds again. The same finding was made by Jin, Wu and Hitt (2017), expanding the conclusion to social media not only impacting the likelihood of funding but also the amount of money raised. Unsurprisingly, the authors (Zhyber et al., 2021) also found that the startup being profit oriented and being B2B rather than B2C oriented is also a positive predictor of fundraising ability.

Garkavenko et al. (2022) used a number of similar factors to Zhyber et al. (2021). However, the goal of the research was twofold: first, the authors were concentrated on the predictive accuracy rather than the interpretability of the models and as a secondary factor, they considered variable importance in the models. Interestingly, the authors (Garkavenko et al., 2022) argued in favor of the use of publicly and freely accessible information for predicting the funding of the startups, due to the human time and effort required for the upkeep of databases with proprietary information thus diminishing the usefulness of the developed models. The research implemented SHAP in order to infer the importance of the variable making findings comparable to Zhyber et al. (2021). Again, various variables were found to be important connecting to the firm's social media presence such as the use of fintech as a hashtag, the specific platforms they had connected accounts on etc. However, with regards to previous funding, number of previous funding rounds, the time passed since the last funding round and the previous funding amount were found to be high impact variables (Garkavenko et al., 2022). However, due to the low interpretability of the models, particularly the statistical significance of the individual variables is not measurable due to the model choice made by Garkavenko et al. (2022).

Additionally, when it comes to literature on specific funding types impacting the likelihood of garnering subsequent funding, research confirms that startups that go through Accelerator Programs increase their chances of receiving VC funding (Dams et al., 2016). The study also demonstrates that accelerated founder teams enhance their social capital, measured by the degree and centrality of their networks. However, this increase in social capital alone does not account for the improvements in financing performance. In fact, the increased likelihood of receiving VC financing is partly explained by the social capital of the founder teams prior to entering the Accelerator Program (Dams et al., 2016).

Expanding the search for literature with success indicators not confined to *funding* success indicators a number of other variables are used for success with partial overlaps with the previously examined literature. Ünal (2019) implemented multiple machine learning models for success prediction finding that the last funding date, the firm's age and the funding lag with regards to the first funding received and the number of funding rounds were the most important variables predicting the success of the firms. Notably however, the results do not stem from models with which the establishment of statistical significance is not possible (Ünal, 2019). The author (Ünal, 2019) also used a number of other variables during the model process such as the sector of the startup and geographic indicators and social media presence The study defines startups that are still operating, have been acquired, or have gone public (IPO) are considered successful (Ünal, 2019). Although again not evaluating funding success specifically and thus the research is not equitable to the aforementioned ones, Eisenmann (2020) evaluated further factors influencing early-stage startup success (defined as changes in equity valuation) including the education of the CEOs finding that conversely to intuition neither an MBA, nor having a degree from a highly ranked university had a statistically significant effect on the short-term success of the firm. Note that Eisenmann (2020), again, did not focus on fintechs specifically, nor was the research focused on the DACH-region. Further research in the area, although not specific to startups, suggested that firms led by CEOs with doctorates were outperforming those with no such educational background in the top leadership position of the firm (Urquhart and Zhang, 2021).

2.6 Due diligence for startup investors

Expanding on the fact highlighted by Garkavenko et al. (2022) that information access can be a significant hinderance for investors, for a multitude of reasons such as the cost of access and the reliability of information gathered by the prospective investors. When considering investing in a prospective startup, investors perform what is called a 'due diligence' process that varies in its level of detail and thoroughness depending on the investor's preferences, abilities and resources and the investees level of cooperation. Whilst public equity investment is regulated and national regulatory bodies require significant disclosure of financial and non-financial information, the private equity market, which venture capital is part of is significantly less regulated and thus the availability and quality of information is less consistent (Jordan, 2006). However, Yung (2009) argues that despite the high-cost nature of the due diligence, it is more effective than merely relying on indirect signals of the quality of investment provided by the entrepreneurs. This efficacy is highlighted by the empirical evidence of the wide-spread use of thorough due diligence processes of the investees by the prospective/potential investors (Yung, 2009). Notably, the author Yung (2009) points out the significant costs associated with it. Due diligence costs can be viewed as a necessary trade off in order to avoid or lower the expected cost of failure of the invested capital (Bushra, Rao and Gulati, 2020). Dixon (1991) further emphasizes this point by examining the techniques used by venture capital funds, revealing that challenges of information asymmetries in the investment process are negatively impacting investors.

2.7 Conclusions from literature review informing the research methodology

Based on the literature review we can conclude the following things, which impact the methodology of the research. We know that:

1. The emergence of fintech has a positive impact on its macro-environment.
2. The primary funding resource for fintech startups is venture capital investment although alternative sources of investments exist such as equity crowdfunding, grants and debt financing.
3. The ability to raise funds for fintech- and other startups alike is a key factor of its survival and ultimately its potential long-term success.
4. The highest risk time where funding access is the most critical for startups (fintechs included) is the time around the valley of death or the period after the initial successful fundraiser.

5. Predictors of successful subsequent fundraising are factors such as details surrounding the initial investment (amount raised, funding lag or in other words the time passed from foundation until the funding, the investors etc.), and qualities and actions of the company such as the vector of the firm etc.
6. Information access and the cost associated with it is an issue for prospective investors and hindering the access of capital for prospective investees.

Knowing this, the goal is to look for factors in DACH-based fintech startups that are accessible for prospective startup investors at minimal cost that have an effect on the likelihood of the given startup's ability to raise funds within one, two, and three years.

2.8 Hypotheses

Based on the aforementioned takeaways from the literature review and the specificities in fintech sectors we formulate the hypotheses of the study connected with the research questions posited in the introduction of the thesis. First with regards to the main research question (**'MRQ'**) and the second research question (**'RQ1'**) we know based on the pre-existing literature that external funding and its qualities are paramount for the success of startups, including fintech startups (Salamzadeh and Kawamorita, 2015; Brown, 2017; Davila, Foster and Gupta, 2003; Kreituss, 2016; Ramalakshmi, 2018; Bednár and Tariskova, 2017; Ritter and Pedersen, 2022), and that previous funding is predictive of subsequent fundraising ability (Zhyber et al., 2021; Garkavenko et al., 2022), thus, we formulate the following hypotheses with regard to the emergent qualities of the initial funding:

H1a: *The initial funding deal size has a positive impact on the subsequent fundraising ability of DACH-based fintech startups.*

H1b: *The number of investors involved in the initial deal has a positive impact on the subsequent fundraising ability of DACH-based fintech startups.*

H1c: *An increase in the time between the foundation date of the DACH-based fintech startups and their initial fundraising date negatively affects their subsequent fundraising ability.*

H1d: *The type of the initial deal of the DACH-based fintech startups affects their subsequent fundraising ability.*

Considering '**RQ2**', based on pre-existing literature it is also clear that differential fundraising patterns prevail when it comes to fintech startups include those in the early stages of business development which can be separated by vectors or sub-segments of the industry (Khajehpour, Mahdi and Yousefi Zenouz, 2020). However, it is unclear whether there are differences in fundraising *ability* across industry vectors. Thus, we formulate the following hypotheses:

H2a: *The vector of the DACH-based fintech startups impacts their subsequent fundraising ability.*

Further, based on the previous works of Zhyber et al. (2021), Garkavenko et al. (2022), and Ünal (2019), we have seen that descriptive factors can be used for predicting startup fundraising. We thus formulate the following hypotheses:

H2b: *The location of DACH-based fintech startups has an impact on their subsequent fundraising ability.*

Additionally, the education of the CEOs of the startups has been investigated as an early-stage success predictor (Eisenmann, 2020), (although not with regards to funding success) leading to the following hypothesis:

H2c: *The level of education of the CEOs of the DACH-based fintech startups has an impact on their subsequent fundraising ability.*

Following similar logic considering '**RQ3**' we formulate the following hypothesis:

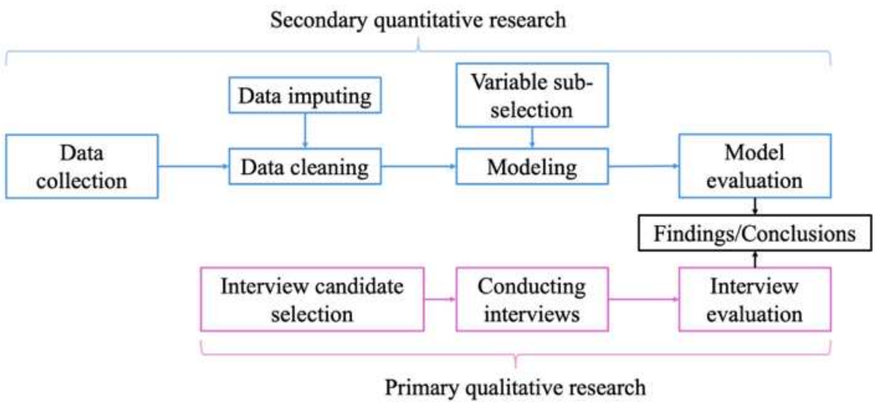
H3: *There are differences between the factors affecting subsequent fundraising of DACH-based fintech startups across time windows.*

3. Methodology and research design

3.1 Overarching design of the research

The objective is to identify the factors contributing to a DACH-based fintech startup's ability to successfully conduct non-debt (grant or equity) fundraising after it initially raised non-debt funds, where the retrieval of these factors must come at a minimal cost and the factors must be publicly accessible, thus answering the research questions and hypotheses. This is a key consideration since, as mentioned previously, significant information asymmetries persist in venture capital investment processes and the retrieval of operational specific data on potential prospective investments is cost and time intensive. Additionally, we also consider factors that emerge in the investment process and can be predictors of the subsequent fundraising ability such as the number of other investors investing in the initial round and the deal sizes, since these do not create additional information asymmetries with the addition of some macroeconomic control variables and a simple year control. A more granular view on variables chosen for the research is elaborated in the following sections on data sourcing and preparation. To enhance the significance and validity of our findings, the research includes validation interviews with both a firm and investor side expert in the field. Please refer to the validation interview sub-chapter for the details on the interview candidate selection and interview process. Note that the interviews aid the validation and interpretation of the quantitative findings, however, for answering the hypotheses conclusively, the quantitative findings prevail. The resulting research and its subsequent conclusions incorporate primary and secondary data collection and limited synthetic data imputing (please refer to the sub-chapter on data imputing):

Figure 4: Resulting research design



Source: Own graphical representation

3.2 Data sourcing

To gain a reliable perspective on the fintech startup field with predictive potential, a data source is needed that has a traceable collection method, thus making it viable for statistical inference. The main data set is sourced from a single source with only limited data sourced additionally to enrich the resulting data set (please refer to the section on data cleaning and variable creation for further details on the external data sourcing). Pitchbook is a good choice due to its semi-automated data collection process where an assurance team reviews the previously collected data points (Pitchbook, 2024). It is also used by many investors whether individual or institutional. We can thus make predictions based on data that fintech investors use to enhance their investment decisions.

Consequently, the core data used for the statistical analysis of the topic and later to draw conclusions from stems from Pitchbook's dataset and particularly from the 's404384953/deals' search. The original dataset is panel data, with at least one but potentially multiple observations for each company as every company has all their respective formal deals included in the dataset. Although over 150 features are available for each observation many of them have a ratio of missing values that renders them unusable for statistical inference and modeling applications. The final features were selected based on their relevance to the research questions and their completeness.

3.3 Overview of resulting initial panel dataset

Based on the aforementioned factors we include the following features in our original (deal level) dataset:

Table 1: Raw retrieved panel data features

Variable name	***Description***
Business status	Reported business status at the time of closing of investment round.
CEO Eduction	Description of the completed higher education programs of the respective CEOs
Company name	Name of the company
Deal date	Date of closing of deal/investment
Deal size	Amount of money raised/invested as part of the deal (in millions of Euros).
Deal status	Whether the deal was completed or is at a different stage such as 'upcoming' or 'postponed'.
Deal type	Designation of deal/investement
Employees	Number of employees at the firm.
HQ location	Location (country and city) of the headquarters of the firm.
Number of Investors	Number of investors in the funding round/deal.
Primary industry code	The reported primary sector the firm is operating in (only one) reported per firm at the time of valuation.
Verticals	All sector verticals the company is operating in (one or more per company) reported per firm at the time of valuation.
Year founded	Year of foundation of the firm.

Source: Own representation, features contained in the original dataset retrieved from https://my.pitchbook.com/search-results/s404384953/deals after further filtering (Pitchbook, 2024).

Although the selected and listed variables include significant amounts of information both at a deal and company level, further filtering and sub-selection is needed before the aggregation process. As the thesis focuses on early-stage startups, the latest stage 'initial' investments considered are Series B. This has been highlighted by the literature review as the last stage of the early-stage investments and is also in concord with Pitchbook's classification of 'early-stage' (Pitchbook, 2024). Due to the significant advancements in technology over the past decades causing significant changes in business models with entire new sectors emerging (such as crypto and AI fintech firms) we place a cutoff on the foundation years in 2010 only examining firms after this point to have as much of a representative result on current investment behavior as possible whilst retaining a number of observations high enough for statistical analysis. We make the following adjustments to the dataset: We filter for firms founded between 2010 and 2020, headquartered in Germany, Austria, or Switzerland, firms that are in the Fintech industry. At a deal level we only include observations where the deal was completed since the interpretation of findings where the deal status is in a different state would be significantly different. Based on the focus of the research, any deals indicating an alternative event in the firm, such as bankruptcy announcements or taking on debt, were omitted. As previously mentioned, debt financing was eliminated due to its ambiguous nature and mixed effects on startup outcomes. After this filtering process, we are left with n = 1983 deal-level observations.

3.4 Defining the dependent variables

After sourcing the initial data, we take additional steps to make the data prepared for use in the modeling step of the thesis. First, we define our dependent variables. This must be done pre-aggregation, since we want to predict an event at t + x (where x is the time between the initial investment and the subsequent one) from information available at t. Subsequently, as a starting point we use the panel data set to define our dependent variables. Although multiple research papers examine various factors influencing subsequent funding rounds and their impacts on the funding amounts (Shetty and Sundaram, 2019, Ling, 2015), they often do not specify a limited timeframe to meet as a success criterion. Although fundraising in most early-stage startups occurs in 12–24-month intervals (Cremades, 2019), differences in verticals within the fintech field can cause deviations in the fundraising pattern (Khajehpour, Mahdi and Yousefi Zenouz, 2020). Thus, we define the dependent variables with an additional margin of deviation and increase the time window as follows: cross-sectional observations are categorized as successful if subsequent to an initial fundraise the firm was able to raise funds again within the following

12, 24, and 36 months, respectively for the three distinct estimated dependent variables. Where again, the subsequent *fundraise must be non-debt fundraise in type (grant or equity)*. Due to the nature of the data some fundraises are classified as separate ones even though the event is misreported as a standalone deal instead of the same one. Thus, we do not consider subsequent fundraises within 100 days of the initial deal circumventing the aforementioned particular issue with the data.

3.5 Data cleaning, variable creation and transformation of the panel dataset

In order to make the dataset more user friendly for data imputing and since the sequence of cleaning variables and one-hot encoding is interchangeable (since we use information observed from the initial investment to predict the occurrence of a second fundraise within the predetermined time frame) we create binary variables for whether or not: the headquarters of the company is located in the capital of the country, the headquarters is located in Switzerland, Germany, or Austria, the education of the CEO of the firm was listed, the CEO of the firm holds a bachelors, masters, or doctorate, or went to an ivy league school. The education variables of the CEOs were manually cross-examined by not only using Pitchbook but also data from LinkedIn (2024). The method is not fully reliable since it is based on self-reporting and the observations go back in time, thus the employment is not listed in all cases as experience. However, the proportion of the degrees of CEOs found was significantly increased. Further, one-hot encoding was applied to the business status and deal type variables to be more usable during the modeling process. Additional binary variables are created on a 'contains' principle for the verticals the company is operating in, with categories created for the seven most popular verticals.

Due to a significant proportion of missing values (87.44%) the employee variable is converted to an 'employees given' binary variable since the firm's willingness and transparency with its staffing numbers might still have explanatory power on our outcome variable.

Additionally, the original panel data contains missing values for the number of investors variable. However, after manual cross-checks it was determined that the missing values were values of 1, thus, they were replaced with 1.

The remaining factor variables are converted to binaries by one-hot encoding, and additionally, a variable is created for measuring the time to the first investment of the company. It is key to keep in mind the limitation of this variable, since due to the way dates of foundations are reported and included on Pitchbook, only the year is reported whereas the deal date itself is accurately reported with a specific day, month, and year. Thus, the difference has a window of potential inaccuracy, making it important to keep in mind during the evaluation and interpretation of the modeling.

As controls and enriching the predictive data, the yearly relevant GDP growth rate and inflation rate were added to the dataset at this stage retrieved from Macrotrends (2024a,b,c,d,e,f) with the addition of the time-relevant federal funds rate for each of the initial deals and a simple year control variable. The former two indicators were sourced on a national annual basis assigned to the individual observations by headquarters location. However, since investors are not confined to the jurisdiction or national boundaries, we use the US federal funds rate as a simplified interest rate indicator from Federal Reserve Bank of New York (2024).

For each company in order to be able to select the correct variables for the cross-sectional dataset a sequential deal indicator in the order of deals was created, meaning that every firm's initial deal is denoted as 1, the second 2 and so on. Additionally, the dependent variable is created and added to the dataset based on the process outlined previously.

The transformation of specific variables in this was done before data imputing so that the predictors of the missing data are as exhaustive as possible.

3.6 Data imputing for deal size with regression tree

Following the creation of the dependent variables, the process to the creation of the final dataset can be continued. The original deal size data discussed variable mentioned above has 41.35% of observations missing which requires the remaining observations to be imputed. According to Pillai, Ramanan and Kumar (2019) using Classification and Regression Trees (CART) can be effectively used to increase data availability without significant compromises to predictive capability or model performance. The implementation of a regression tree (for data imputing) also comes with the benefit of intuitive understanding of the model's decision-making process (De'ath and Fabricius, 2000). The regression tree algorithm is able to automatically decide on the splitting variables and specific split-points by implementing the following process:

1. Our imputing model is given by the function $f(x)$ that sums up the products of constants c_m and the indicator function of $I(x \in R_m)$ for M regions. The goal is to find constants c_m that minimize our prediction error for deal size.
2. To find the best c_m, in this case denoted as $\widehat{c_m}$, the algorithm computes the average of the observed y_i within the same region R_m. When subtracting this value from each y_i and squared, it results in the smallest possible sum of squares within the region.
3. Due to computational limitations finding the optimal binary partition point, the regression tree employs a greedy algorithm This involves splitting the data with a chosen variable j at a split point s, defining two new regions $R_1(j,s)=\{x \mid X_j \leq s\}$ and $R_2(j,s)=\{x \mid X_j > s\}$.
4. The algorithm finds the variable j and split point s that minimize the sum of squared errors within each of the subsets. We can express this by:

$$\min_{j,s}\left[\min_{c_1}\sum_{x_i\in R_1(j,s)}(y_i - c_1)^2 + \min_{c_2}\sum_{x_i\in R_2(j,s)}(y_i - c_2)^2\right]$$

5. The averages for the optimal solution ($\widehat{c_1}$ and $\widehat{c_2}$) for each subset respectively are found by inner minimization:

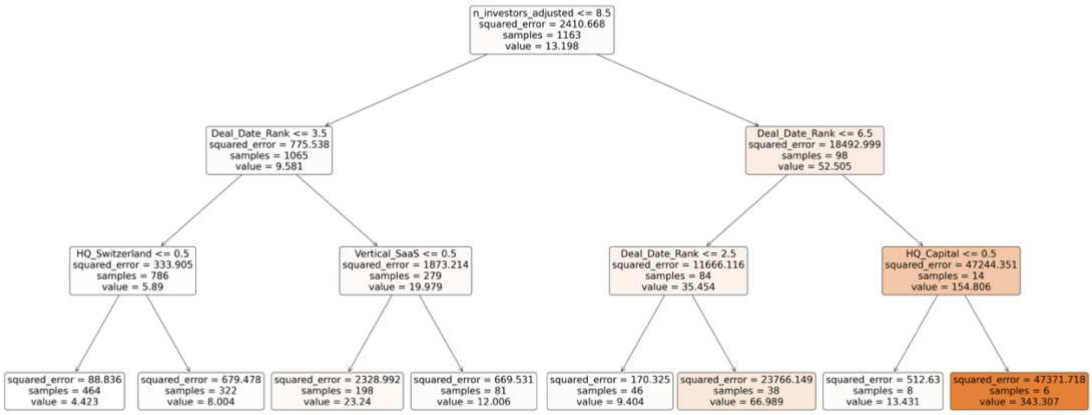
$$\widehat{c_1} = \mathrm{ave}\big(\, y_i \mid x_i \in R_1(j,s)\,\big) \quad \text{and} \quad \widehat{c_2} = \mathrm{ave}\big(\, y_i \mid x_i \in R_2(j,s)\,\big)$$

6. This process is then repeated for each subset created creating smaller and smaller partitions.

Based on Hastie, Tibshirani and Friedman (2009)

This leaves us with a more granular imputing method compared to using the median or mean of the values since we can take other independent variables and predict the missing values where $\widehat{c_m}$ takes a value minimizing the sum of squares of the y_i of the leaf. In order to avoid overfitting, we take a conservative approach setting the hyperparameters of the model to minimum samples per leaf = 3 and maximum depth of tree =3. The imputation process was done pre-aggregation due to the increased training size of the data.

Figure 5: Regression tree estimate for deal size data imputing



Regression tree model visualization for imputing missing data points for the deal size variable (R^2 = 0.30)
Source: Own graphical representation

3.7 Data aggregation

The aggregation or also referred to as the collapsing of the data in this particular case is a simple process since the only purpose of the longitudinal nature of the dataset is to allow the creation of the time dependent outcome variables. Thus, beyond the outcome variables the variables that are not designated as 1 in the sequential indicator are omitted from the cross-sectional dataset. The resulting dataset contains the observation of information from time t with the addition of the dependent variables.

3.8 Overview of resulting dataset and descriptive statistics

The resulting dataset contains n = 543 values, with a successful subsequent fundraising round closed within one year for 141 firms, a successful subsequent fundraising round closed within two years for 274 firms, and a successful subsequent fundraising round closed within three years for 334 firms.

Looking at a location split of the fintech firms within the sample, 289 firms were located in Germany making up 53,2% of the sample, 45 firms were located in Austria making up 8,3% of the sample and 209 were located in Switzerland making 38,5% of the sample. Notably, only 31,8% of firms in the sample were headquarted in a capital city.

The initial deals observed within the dataset as expected for first round fundraising were overwhelmingly (>75%) composed of three deal types: 'accelerator/incubator', 'seed-round investment', and 'early-stage VC investment'. This is completely in line with expectations, since these are common funding types for initial fundraising. The discrepancy between them can be caused by a multitude of factors such as the verticals the firm is operating in and the usual fundraising patterns thereof, but also idiosyncratic self-reported designations since the categories potentially contain overlaps.

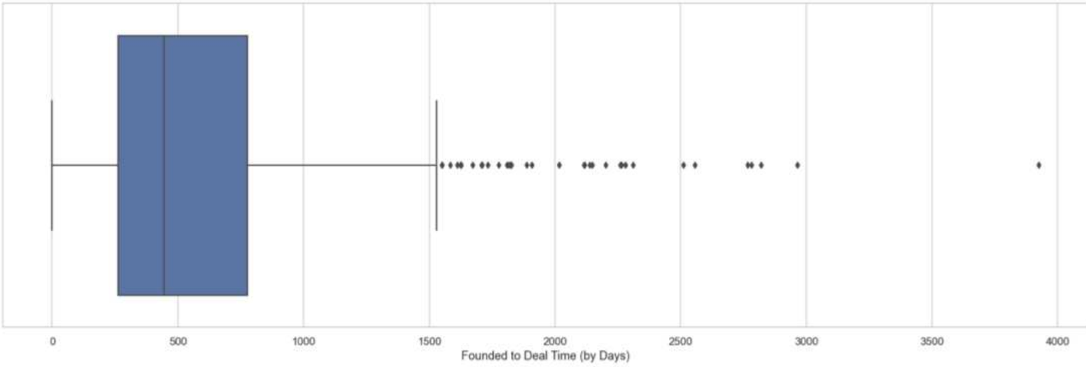
When it comes to the vertical specific indicators, it is important to note that one firm can be present in multiple verticals. The most popular verticals in the sample are 'TMT', 'SaaS', and 'Crypto', one which 80.5% of firms in the sample were part of.

Examining the education specific variables, we can observe that 87.9% of the CEOs had publicly retrievable degrees with over 60% having completed a bachelor's education and over 40% having completed a master's education. Note, that a master's degree does not necessarily mean a completed bachelor's education, since some education systems have integrated master's programs without issuing a separate bachelor's degree. Both the indicator for having received a degree from an ivy league school and the indicator of having completed a doctoral degree showed lower means with <6% and <16%, respectively. The measures are not fully reliable, since as mentioned the data was partially sourced manually through LinkedIn (2024).

Looking at the reported business status of the DACH-based fintech startups at the time of the initial deal, >90% were reported as either 'generating revenue' or being in the 'startup' phase which designates the status of the firm in the initial development not yet generating revenue. Notably, 53.6% of the firms were reported as generating revenue at the time of the initial investment.

Although the data contains some outliers particularly in the variable examining the time (in days) the startup took from foundation until the closing of the initial investment this measure is valid (although with a year of uncertainty, as described during the creation process) and potentially holds explanatory power and is especially important in the case of nascent entrepreneurs (early-stage ventures) (Warhuus, Frid and Gartner, 2021).

Figure 6: Boxplot of difference of time between foundation until first funding

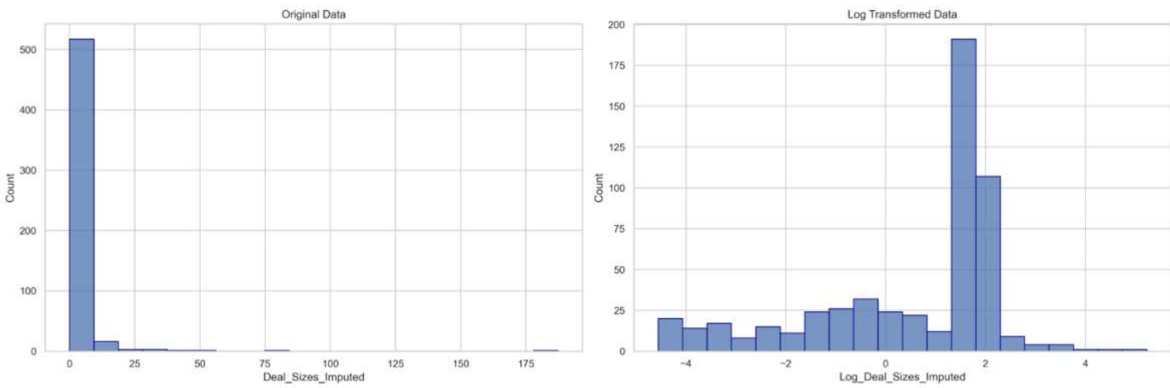


Source: Own graphical representation

The maximum value the aforementioned variable takes in the sample is 3927, with a mean value of 599 and a standard deviation of 542,3 which is a realistic measure considering the industry and the variety of verticals and business models encompassed in fintech. This means that on average within the sample it takes over a year and a half before startup funders are able to secure their first formal funding.

Inspecting the data we can see that the previously imputed deal size variable is severely right skewed which is expected, since the variable is reflecting a nominal financial measure. Thus, a log conversion is performed.

Figure 7: Histogram for deal size log transformation



Source: Own graphical representation

It is clear that although there is a significant concentration around the value of 2 in the log transformed variable, it is much more favorable to use in modeling due the distribution of values than the initial data pre-transformation variable. The resulting variable has a mean of

0.46 with a standard deviation of 1,959 suggesting a significant dispersion of values within the sample. A similar 'positive skew' was discovered when analyzing the variable describing the number of investors investing in the initial fundraising event/deal and the variable describing the time it took for the first investment to occur from the foundation date (as partially seen in 'Figure 5'). This is also expected, since many early-stage startups and startups in general raising an initial investment round receive funding from only one investor rather than multiple. These variables were subsequently also converted to logarithmic form (refer to 'Appendix D' and 'Appendix E'), however, for the former a positive skew (although less severe) remains due to the high number of '1' values explained by $\log_{10}(1) = 0$. Please refer to 'Appendix F' for a more nuanced view of the continuous variables related to the initial deal details in boxplot form, both in unaltered and logarithmic form with regards to the respective dependent variables. The 'model estimation' sub-chapter further elaborates on the final choice of logarithmic versus non-transformed versions of the variables.

Examining the dependent variables, we can see that none of them are severely imbalanced, since percentage of observations designated as successful is 26,0%, 50,5%, and 61,3% respectively for securing subsequent funding within 1, 2, and 3 years. These ratios are significantly higher than datasets where success is defined in a more long-term manner and studies examining general startup survival after foundation or eventual securing of funding such as in the works of Sharchilev et al. (2018). This is caused by the fact that the sample used is not a sample of all fintech startups founded in DACH-region but rather those that already have raised funds once successfully.

Although the thesis does not look at longitudinal effects, it is possible to make some observations on the data looking from a temporal perspective. Referring to 'Appendix C' the conclusion can be made that with the exception of firms closing initial fundraising rounds in 2012 having been more successful at securing subsequent funding, the dependent variables are fairly stable over time suggesting that the subsequent-to-first-round fundraising ability of fintech in the DACH firms did not change significantly over time within the observed time frame of firms closing their initial round between 2010 and 2020. What is notable is that over time it is clear that many startups are not receiving subsequent funding within one year of the first investment however, the delta between receiving funding within two and three years is very consistent and low. Suggesting that the assumption of the fundraising pattern was not erroneous.

The summary statistics for the final dataset can be found in ‘Appendix A’.

3.9 Model choice

As alluded to the thesis is focused on binary outcome variables. The two specific criteria the model must fulfil is the ability to model a binary variable (binary classification) and it has to provide highly interpretable and transparent in the process. It is also key that the model provides an output to be subsequently used for factor analysis. All the aforementioned criteria are fulfilled by *logistic regression*. Multiple other classification models have been used for predicting various success factors related to startups such as tree models and ensemble learning models (random forests, gradient boosting), with many of them outperforming logistic regression measured by multiple predictive performance metrics, however, due to our focus on finding statistically significant features, and not analyzing variable magnitude in prediction, and predictive accuracy achievable, logistic regression is implemented.

1. When logistic regression is in use predicting a binary variable, the following formula describes the predicted values:

$$\Lambda(z) = \frac{1}{1 + e^{-z}}$$

It takes real valued number and ‘squashes’ it into a range of (0,1). This is used to circumvent the problem with the implementation of linear probability models, where theoretically predicted values can be >1 and <0.

2. In a particular case (which is applicable to the dependent variables in use since the occurrence of success is =1 and =0 otherwise) the resulting probability estimation can be describes as:

$$P(\, y = 1 \mid x\,) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)}}$$

and

$$P(\, y = 0 \mid x\,) = 1 - \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)}}$$

Where the β_0, β_1, β_2 ,…, β_k represent the estimate for the coefficients, x_1, x_2,…, x_k represent the predictors and e is the base of the natural logarithm ≈ 2.718.

3. The coefficients of the model are estimated by using the maximum likelihood method. The methods finds parameter estimates that maximize the sum of logarithms of the $f_i(\beta_0, \beta_1,\ldots, \beta_k)$ where i stands for the i-th element in the sample. Intuitively, the method finds

estimates such that the predicted probability of success (in this case, subsequent fundraising success) for each fintech startup corresponds as closely as possible to the startup's observed subsequent fundraising success.

4. The implementation of the logistic regression operates under several assumptions.
   i) The outcome variable has to be binary, in this case the dependent variables are encoded as 0 and 1, fulfilling this requirement.
   ii) The relationship between the log odds of the outcome and the predictor variables is assumed to be linear.
   iii) Absence of perfect multicollinearity amongst the explanatory variables.
   iv) Large sample size however, the number of cases of the less frequent outcome for each predictor in the model varies, a rule of thumb being a commonly cited number being 10.
   v) No significant explanatory variables are left out of the model formulation and that the included predictors are in their correct form or interaction terms.
   vi) Predictors do not contain any significantly influential outliers within the sample.
   vii) the variance of the response variable is a function of the mean, specifically describes as *p(1-p)* where *p* is the predicted probability of the outcome.

Based on Stoltzfus (2011), Kahale (2024), Hastie, Tibshirani and Friedman (2009), and James et al. (2013).

Variable sub-selection is a topic of discussion with multiple approaches such as purposeful selection and step wise selection (Wang, Zhang and Bakhai, 2004, Bursac et al., 2008). Due to the large number of variables implementable in the logistic regression predictors (>40) and the relatively small sample size of n=543, the question whether or not variable sub-selection is necessary arises. Due to the number of independent variables in our dataset, using all of them in the same model can lead to overfitting and the reduced reported statistical significance of the individual independent variables. Thus, the implementation of a mechanism of variable elimination is needed. In order to make this process interpretable and transparent a backwards elimination (stepwise selection) is implemented. This process involves first estimating a model with all viable variables included and then eliminating the variable with the lowest statistical significance (highest value for p>|z|) and then re-estimating the model. Finally, this process is repeated until the model only includes variables that are statistically significant to the pre-specified threshold (usually 1, 5, or 10%) (Bursac et al., 2008). The study implements a 5%

cutoff in line with the industry standard (Cowles and Davis, 1982). Please refer to 'Appendix A' for the list of all variables which serves as the starting point in the modeling process.

Note that throughout the analysis, the significance levels refer to the z-test (or Wald test). These tests are used to determine the statistical significance of the coefficients in the logistic regression models (Eberly College of Science, Pennsylvania State University, 2018). It is also key to note that both the models with backwards eliminated variables and the models with all viable variables are evaluated since both have inherent upsides and downsides.

The models' goodness of fit is evaluated using McFadden's Pseudo R-squared measure, which measures how much of the variation in the dependent variable is explained by the independent variables in the model. The measure is defined as: $R^2_{\text{McF}} = 1 - \frac{\ln(L_M)}{\ln(L_0)}$, where $\ln(L_M)$ is the log-likelihood of the fitted model and $\ln(L_0)$ is the log-likelihood of the null model, which is a model with no predictors (only an intercept) (McFadden, 1974).

3.10 Cross-validation interview process

In order to be able to properly cross-validate our findings primary research is conducted in the form of two semi-structured expert interviews. Since the findings of the statistical analysis mainly concern two parties (investors and investees/startups) the candidate selection is focused on receiving insights from both the investor and the startup side. In particular, it is important since the perception of the two parties might be divergent. Since a semi-structured interview process is implemented, a set of pre-determined questions are posed to the interviewee which are then answered. However, the semi structured nature allows the interviewer to further probe the subject on details of their answer and allows the interviewee to elaborate beyond the confines of a more structured approach (Barclay, 2018). In this case, candidate selection occurs through a pre-existing set of prospects on LinkedIn, on both the investor and investee side, which is then narrowed down by convenience based on candidate consent and availability. For the emergence of comparable results, the same set of questions are used with the same recording techniques. The interviews are subsequently evaluated. The questions are centered around the perception of the interviewees of the factors evaluated statistically, so the validity of the statistical findings can be fully confirmed or called in question. Specifically, due to the more consequential timeframe which is encompassing the general time window of early-stage startup fundraising cycles (Schulz, 2024, Cremades, 2019), the validation interviews focus on the findings from the three-year timeframe but include sections on the differences of factors by time windows. For further details on the selected individuals for the validation interviews, please refer to 'Appendix N'. For the interview guide and the summary of responses please refer to 'Appendix O'.

4. Quantitative analysis results

4.1 Model estimation

Before estimating separate models using the backwards elimination method described in the model choice section, a model with all viable variables is estimated. The models estimated using all variables are designated by the number of years the dependent variable is taking into account for subsequent fundraising and 'a' (i.e 1a, 2a, 3a). However, before estimating, an initial sub-selection of the variables is done to eliminate variables with high multicollinearity. The visualization for the correlations in the dataset is visible in 'Appendix H'. Beyond excluding variables due to high multicollinearity (>0.8), the model with 'all' variables also excludes predictors that cause separation or 'perfect prediction'. These variables do not allow for variability in the data and are thus excluded. When it comes to the decision to use the logarithmic or standard (non-converted) versions of the variables that were previously converted, due to the resulting distributions of the variables only the deal size variable is used in its logarithmic form. Although it is technically feasible to use both the logarithmic and standard form of the given variables in the same model, it increases complexity in inference.
Variables with high (>0.8) collinearity amongst are also eliminated along with variables causing separation effect. Using these exceptions, the models with all remaining variables are estimated for each of the dependent variables. For testing the assumptions of logistic regression beyond eliminating high collinearity amongst the predictors, Hosmer-Lemeshow tests and specification link tests are conducted.

When it comes to Hosmer-Lemeshow tests, we cannot reject the associated null hypothesis that there is no difference between the observed and expected frequencies in the logistic regression model at a 5% significance level. In other words, the test results suggest for each of the models a good calibration between the predicted probabilities from the model and the observed outcomes, suggesting that there is no significant evidence to suggest that the model poorly fits the data. Please refer to 'Appendix I' for the results.

After conducting the aforementioned Hosmer-Lemeshow tests, link tests are conducted to gauge whether or not the model is mis-specified, looking specifically at whether or not the predicted values (hat) or the square of the predicted values (hat squared) is a statistically significant predictor of the given dependent variable. In all three cases (success of subsequent fundraising within 1, 2, and 3 years) the hat (predicted values) are statistically significant at $p < 1\%$ and the hat squares (predictors squared) are not statistically significant at even a 10% significance level. These results suggest that the model specification is appropriate.

When it comes to the model estimation using the backwards elimination method based on the process described in the model choice chapter, the previously (for models 'a') pre-selected variables are considered. The models estimated using all variables are designated by the number of years the dependent variable is taking into account for subsequent fundraising and 'b' (i.e 1b, 2b, 3b). The further variable elimination is done using an automated process (please refer to 'Appendix K' for the Python code used for implementation details). Hosmer-Lemeshow tests and specification link tests are conducted again for each of the newly estimated models. As in the case of the models including all viable variables, the associated null hypothesis that there is no difference between the observed and expected frequencies in the logistic regression model cannot be rejected at a 5% significance level. The model specification link test also shows the similar levels of robustness as the previously estimated 'a' models (please refer to 'Appendix M' for the detailed link test).

It should be pointed out that all models were observed to be jointly significant at a 5% significance level.

4.2 Logistic regression results for subsequent funding within one year

Table 2: Logistic regression output with dependent variable considering a 1-year time window

variables	*(1a, with all viable variables)* *dependent_var_1_year*	*(1b, with backwards eliminated variables)* *dependent_var_1_year*
log_deal_sizes_imputed		-0.139***
		(0.0508)
n_investors_adjusted	0.0881**	0.0988***
	(0.0421)	(0.0370)
employees_given_binary	0.885**	
	(0.408)	
vertical_tmt_binary	0.554**	0.472**
	(0.271)	(0.212)
deal_type_earlystagevc_binary		-0.625**
		(0.264)
deal_type_grant_binary	2.701**	
	(1.207)	
Constant	-224.0	-1.230***
	(180.8)	(0.154)
Hosmer-Lemeshow test result	Prob > chi2 = 0.0575	Prob > chi2 = 0.1668
McFadden's Pseudo R-squared value	0.094	0.0436
Observations	543	543

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Own representation, output of 1a reduced to only include variables significant at 5% or lower levels, please refer to 'Appendix I' for the full output of the 'a' logistic regressions (please refer to Appendix A for the full definition of all variables).

Examining the results from the model estimates starting with model one, only variables that are significant at a 5% significance level are considered for inference following the industry standard (Cowles and Davis, 1982). Note that due to high collinearity 'business_status_productdevelopment_binary' and 'hq_switzerland_binary' are omitted, and due to separation (perfect prediction) 'business_status_profitable_binary', 'business_status_stealth_binary', and 'business_status_productinbeta_binary' are omitted. The outcome variable is defined as =1 if the startup was able to raise funds within one year of the initial fundraise. However, it is important to mention the dichotomous driving forces of fundraising. As the usual fundraising cycle for startups is often longer than one year (Cremades, 2019) it is difficult to make conclusive inference on the results related to drivers of funding. The two driving forces of achieving funding or not are both the urgency (or need) and the ability to raise funds. It is not necessarily the case within this timeframe that a given (fintech) startup wants to raise funds (Schulz, 2024). Taking this into consideration we can draw more accurate conclusions from the regression outputs. It is also important to note that we consider all of the described effects as 'ceteris paribus' effects.

The coefficient associated with the initial deal size (in log form) negative and statistically significant at a 1% significance level, meaning that fintech startups that receive a smaller initial initial investment are more likely to raise funds again within one year. This is a notable finding, since this means that DACH-based fintech startups that are unable to raise sufficient funds seek and can secure funding within one year. Notably however, the same finding is not made when all variables are considered.

The coefficient of the variable describing the number of investors from the initial fundraising round is positive and statistically significant at a 5% and 1% significance level in both 'a' and 'b' models, respectively. Meaning that a higher number of investors present in the initial fundraising round increases the chances of closing a subsequent round within one year. Again, this suggests a short-term effect that is limited to the fundraising pattern outside of the generally perceived funding cycle for startups (Schulz, 2024, Cremades, 2019).

Looking at the coefficient associated with 'employees_given_binary', it is positive and statistically significant at a 5% significance level. The interpretation of the positive relationship is more nuanced than the name of the coefficient suggests (please refer to 'Appendix A' for variable definitions), since it infers that fintech startups that publicly disclose their employee numbers are more likely to successfully raise funds within one year of the initial fundraising. This is possible due to two reasons. First, startups seeking funding in the short term are more inclined to disclose staffing information publicly. Second, investors are more inclined to invest in startups that are more public about their staffing information. Again, it is not possible to make conclusive inferences on the *ability* to raise funds due to the limited time frame of reinvestment (one year) at this stage of the study.

Examining vertical specific variables predictive of subsequent funding success, it can be observed that the coefficient for 'vertical_tmt_binary' is positive and statistically significant at a 5% level suggesting that fintech startups that specialize in or are offering products and services in technology, media, and telecom (TMT) were more likely to complete a subsequent fundraising round within one year of the original round. The relationship is observed in both model estimates, in line with the finding that sectoral differences amongst fintech startups prevail when it comes to fundraising (Khajehpour, Mahdi and Yousefi Zenouz, 2020). However, again the pattern suggests that TMT focused fintech startups are more likely to raise funds within one year of the initial fundraiser, which is not necessarily a qualitatively positive sign since the timeframe is below the usual funding cycle as mentioned before (Schulz, 2024, Cremades, 2019).

When it comes to the impact of the deal type on subsequent funding within one year, two deal types were found to be statistically significant ($p<5\%$) predictors. First, it is observed from model 1b, that firms receiving early-stage venture capital investment ('deal_type_earlystagevc_binary') as their first formal investment are less likely to raise funds within a year. However, the aforementioned effect is only observed in the model estimate with eliminated variables. On the other hand, the coefficient may be statistically significant because it is capturing the effect that is otherwise expressed by the independent (in this case can be considered as control) variables in model 1a. The second variable found to have a statistically significant ($p<5\%$) effect on the dependent variable is 'deal_type_grant_binary'. The coefficient suggests that firms receiving a grant as their first form of funding are more likely to receive subsequent funding within one year of receiving the grant. Note however, that grants make up only a small proportion of the sample (~ 3.3%)

All other variables were observed to not be significant at a 5% level. The non-significant variable coefficients include all coefficient associated with macro-economic indicators (effective federal funds rate, inflation rate, and GDP growth rate), which are thus omitted from model 1b during the variable backwards selection process. Note that the inference of the effects is limited by the fundraising pattern of fintechs where, as discussed in the literature review, fintech startups in different verticals seek funding at different times from different sources. The one-year time window is below the usual funding cycle of startups, meaning that generally startups do not seek funding within this period (Schulz, 2024). Assessing the overall performance of the models, we observe Pseudo R-squared values of 0.094 and 0.044, respectively. This means that models 1a and 1b capture approximately 9.4% and 4.4% of the variation in the dependent variable, respectively. The difference in R-squared values is potentially partially explained by overfitting in the case of model 1b. The values are fairly low, meaning that while the models do have some predictive power, they do not explain a large portion of the variability in the outcome.

4.3 Logistic regression results for subsequent funding within two years

Table 3: Logistic regression output with dependent variable considering a 2-year time window

variables	(2a, with all viable variables) dependent_var_2_years	(2b, with backwards eliminated variables) dependent_var_2_years
n_investors_adjusted		0.0994**
		(0.0392)
business_status_startup_binary	0.456**	
	(0.207)	
ceo_educ_bachelor_binary		0.457**
		(0.192)
vertical_mobile_binary		0.498**
		(0.242)
vertical_crypto_binary	-0.538**	-0.567***
	(0.241)	(0.212)
deal_type_grant_binary		1.457**
		(0.584)
Constant	-232.5	-0.0450
	(161.9)	(0.174)
Hosmer-Lemeshow test result	Prob > chi2 = 0.1319	Prob > chi2 = 0.6212
McFadden's Pseudo R-squared value	0.1068	0.0548
Observations	543	543

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Own representation, output of 2a reduced to only include variables significant at 5% or lower levels, please refer to 'Appendix I' for the full output of the 'a' logistic regressions (please refer to Appendix A for the full definition of all variables).

As opposed to the previously predicted dependent variable of fundraising success within one year, the second models ('2a' and '2b') increase the time window to considering fundraising success within two years of the initial fundraising deal. Thus, the outcome variable is defined as =1 if the startup was able to raise funds within two years of the initial fundraise. This timeframe is of key importance, since it encompasses what is considered as the general early-stage funding cycle for startups (Schulz, 2024, Cremades, 2019).

The second model (2a) includes all viable variables, omitting variables with high collinearity or separation effect. The 'business_status_stealth_binary' variable is omitted due to the latter reason and 'hq_switzerland_binary' and 'business_status_generatingrevenue_binary'are omitted due to the former. Model 2b is again implementing the backwards elimination process only including variables with the industry standard 5% (Cowles and Davis, 1982) significance level starting with the variables included in model 2a. The 5% significance level cutoff is implemented again for considering variables as statistically significant in model 2a. As in the case of the previous timeframe, the effects are to be considered as 'ceteris paribus' effects.

In accordance with model 1b where model estimate showed positive relationship between the number of investors in the initial fundraiser and subsequent fundraising within one year, the same is reflected in model 2b. Thus, the higher the number of investors in the initial round of fundraising, the higher the likelihood that the startup is going to raise funds again within two years. The coefficient meets the statistical significance requirement (p<5%), although notably, the relationship is only reflected in the model with the backwards eliminated variables (2b).

When it comes to business status indicators at the time of initial investment, one reported business status at the time of the initial fundraiser is found to be predictive on subsequent investment within two years. Model '2a' shows that firms in the initial development phase and that are not yet generating revenue at the time of the first investment ('business_status_startup_binary') are more likely to receive subsequent funding within two years of the initial fundraising compared to firms that were not classified in this business status category. The coefficient estimate is positive and statistically significant at a 5% significance level. Notably however, the relationship is only reflected in the model with all viable variables included ('2a').

Looking at the indicators of the startup's CEO's education, it is observed from model '2b' that holding a bachelor's degree has positive predictive power on the likelihood of subsequent fundraising within two years. However, the effect is not reflected in model '2a'. Thus it is possible that the coefficient estimate is capturing effects otherwise explained by the other variables in model '2a'. As indicated by the interpretation, the coefficient is positive and statistically significant at a 5% significance level.

Examining vertical specific effects on fundraising success within two years of foundation, two variables are found to have statistically significant predictive power on the dependent variable. First, fintech startups providing services for mobile devices and/or enabling mobile communication are more likely to raise funding within two years of the initial fundraise. The coefficient estimate is positive and statistically significant at a 5% significance level, although the same limitation applies as for the previously examined effect since the variable is only found to be significant by the backwards eliminated model ('2b'). Second, both '2a' and '2b' models suggest (negative sign of coefficient for and statistically significant at 5% and 1% significance levels, respectively) that fintech startups in the crypto sub-segment of the industry or 'vertical', are less likely to raise funds again within the two-year time window. The robustness of the finding can further be underlined by the fact that the coefficients in both models are of similar magnitudes (-0.54 and -0.57 in '2a' and '2b', respectively). However, this can be partially explained by the fact that crypto focused startups have the ability to raise funds through initial crypto offerings (ICO) rather than formal venture capital investment (Hartmann, Wang and Lunesu, 2018). This would not be reflected in the sample of this study.

When it comes to deal types being predictors of subsequent funding within two years of the initial fundraising, having received a grant ('deal_type_grant_binary') shows statistically significant (p<5%) a positive coefficient estimate and suggests that DACH-based fintech startups that received a grant as their first formal fundraising were more likely to receive funding within two years of the initial fundraising. This is in line with the findings with model 1a, however, in the case of the two-year time window the effect is only observed in model 2b, which might be capturing effects of missing controls, since the relationship is not observed in model 2a. Again however, as before, note the small proportion of grant as the initial deal in the sample.

As before, all variables not discussed did not meet the (p<5%) statistical significance criterion, including all macro-economic variables. Notably, the interpretation of the effects observed in models '2a' and '2b' is different since the two-year time window covers the general fundraising cycle of early-stage startups (Schulz, 2024, Cremades, 2019). Overall, the performance of the models shows marginal improvement over the previously examined ('1a', '1b') models respectively, with model '2a' capturing approximately 10.7% of the variation in the dependent variable, whilst '2b' captures approximately 5.5%.

4.4 Logistic regression results for subsequent funding within three years

Table 4: Logistic regression output with dependent variable considering a 3-year time window

variables	*(3a, with all viable variables)* *dependent_var_3_years*	*(3b, with backwards eliminated variables)* *dependent_var_3_years*
founded_to_deal_time		-0.000529***
		(0.000183)
hq_capital_binary	0.652**	0.492**
	(0.269)	(0.210)
business_status_startup_binary		0.434**
		(0.200)
ceo_educ_bachelor_binary		0.602***
		(0.211)
ceo_educ_doctorate_binary	0.850**	0.954***
	(0.389)	(0.349)
vertical_crypto_binary	-0.569**	-0.574***
	(0.243)	(0.212)
vertical_saas_binary	0.537**	0.597***
	(0.241)	(0.227)
deal_type_acceleratorincubator_binary		-0.584***
		(0.206)
Constant	-103.2	0.365
	(170.2)	(0.233)
Hosmer-Lemeshow test result	Prob > chi2 = 0.1190	Prob > chi2 = 0.3407
McFadden's Pseudo R-squared value	0.1353	0.0958
Observations	543	543

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Own representation, output of 3a reduced to only include variables significant at 5% or lower levels, please refer to 'Appendix I' for the full output of the 'a' logistic regressions (please refer to Appendix A for the full definition of all variables).

The result from models '3a' and '3b' can be considered as the most conclusive since they not only capture the usual time window for early-stage fundraising but go beyond by adding a one-year margin. This means, that the model captures funding success for companies including deviations in funding patterns and anomalies in fundraising preference. The outcome variable in this case is defined as =1 if the startup was able to raise funds within three years of the initial fundraise. As previously, the cutoff for statistical significance is p<5% (Cowles and Davis, 1982). It should be emphasized that due to the time window the dependent variable captures, in this section it is appropriate to assume the willingness to raise funds from the investee side, since it captures the range beyond the usual fundraising time for early-stage startups. Although some exceptions apply, since there are fintech startups in the early stages of their operations that are able to secure financing through alternative channels that are not included in the success category.

By examining the statistically significant coefficients in model '3b', it is evident that organizations which raised funds more slowly initially ($p<1\%$) were less likely to secure subsequent funds successfully within a three-year period following their initial fundraising event. Note that the magnitude of the coefficient is small, this is caused by the continuous nature of the variable and due to it being on a day basis.

When it comes to location-based indicators, both ‘3a’ and ‘3b’ models indicate a statistically significant positive effect of the firms being headquartered in the capital of the given country as opposed to not (‘hq_capital_binary’) on the ability to raise funds within three years of the initial deal. Although location-based indicators have been investigated with respect to more general success metrics of startups (Ünal, 2019, Garkavenko et al., 2022), a statistically significant positive relationship between being located in the capital of the country and fundraising success has not previously been established regardless of the funding timeframe. It is also and indicative of the robustness of the finding that it is reflected in both the backwards eliminated (‘3b’) and the model including all viable variables (‘3a’) and that the coefficient magnitude is similar (0.65 and 0.49).

Examining the effect of the DACH-based fintech CEO’s education on the likelihood of receiving two types have been shown to have a statistically significant effect ($p<5\%$). First, the positive coefficient of ‘ceo_educ_bachelor_binary’ indicates that firms that are led by CEOs that have a bachelor’s degree (and have publicly disclosed it) are more likely to secure funding again within three years of the initial fundraiser. The effect is significant at a 1% significance level, however, as in the case of the models considering a two-year time window it is only reflected in the backwards eliminated model (‘3b’). Second, it is observed from both models (‘3a’ and ‘3b’) that having a doctorate (‘ceo_educ_doctorate_binary’) is a positive predictor of receiving funding within three years of the initial deal. This finding is highly robust, as evidenced by the positive effect being significant at $p<0.05$ in both models (‘3a’ and ‘3b’), with similar coefficient magnitudes of 0.85 and 0.95. The statistically significant finding with regards to the bachelor’s degree is in line with the findings when considering a shorter two-year time frame. It is important to note that the indicator can be influenced by selection bias due to the self-reported information.

Looking at the vertical specific variables similar levels of robustness are observed. Again, two statistically significant relationships are shown in models '3a' and '3b'. First, echoing the findings from models investigating a two-year time window ('2a' and '2b'), we see a statistically significant (p<5% and p<1%, respectively) negative effect of the firm focusing on the crypto sub-segment ('vertical_crypto_binary') on the likelihood of fundraising ability within three years of similar magnitudes compared to the previous model estimates. This, as stated previously is not necessarily caused by the inability of the firm to raise funds within the time window but rather the fact that crypto focused fintech startups have ICOs as an option for raising funds in the early stages of developing the business (Hartmann, Wang and Lunesu, 2018). Second, it can be observed from the statistically significant (p<5% and p<1%, respectively in models '2a' and '2b') positive coefficient estimates of 'vertical_saas_binary' that firms offering software as a service are more likely to receive subsequent funding within three years compared to the firms that are not.

When it comes to the effect of the initial on subsequent funding ability, only one type showed a statistically significant effect on the ability to raise funds within three years after the initial fundraiser. DACH-based fintech startups that were initially funded by accelerators or incubators are less likely to raise funds again within three years of the initial deal. This is indicated by the statistically significant (p<1%) negative coefficient estimate associated with the variable 'deal_type_acceleratorincubator_binary'.

As before, all other variables that were not discussed in this section were found not to be statistically significant and thus it is not possible to reject the associated null hypotheses that the variables have no impact on the outcome (subsequent funding success within three years in this case) at a 5% significance level. The indicated effects are the most consequential from both the investee and investor point of view, since they are observed in a timeframe (Schulz, 2024, Cremades, 2019) where it is fair to assume that fintech startups attempt to raise funds. When it comes to the overall performance of the model an improvement in the McFadden Pseudo R-squared value can be observed suggesting that models '3a' and '3b' capturing approximately 13.5% and 9.6% of the variation in the dependent variable, respectively.

Beyond the observed variables affecting the likelihood of subsequent fundraising, it is also important to point out the effects that could not be determined to be statistically significant. As previously alluded to, when it comes the *ability* to raise funds, the three-year time window is the most consequential timeframe, since it encompasses the usual target window for fundraising. Thus, it is used for assessing the effects not observed in the models ('3a' and '3b').

None of the models including '3a' and '3b' found a statistically significant relationship between the firm focusing on B2B customers ('vertical_b2b_binary') rather than not. Thus, the quantitative findings from the sample of the present do not overlap with the findings of Zhyber et al. (2021) where a positive relationship was found. Although the coefficient estimate present in model '3b' is positive the associated null hypothesis that the coefficient is =0 cannot be rejected at even a 10% significance level.

Further, it is important to mention that even though they were included in every 'a' model and in the backwards elimination process of the 'b' models, included macro-controls (GDP growth rate, inflation rate, and federal funds rate) did not show statistical significance at a 5% significance level. Although in the case of the 'a' models the coefficient estimate for the federal funds rate ('fed_rate') was consistently negative. This is line with the case of the simple year control, which also did not show statistical significance at even a 10% level. This suggests that there is no clear statistically significant increase or decrease in the likelihood of receiving funding within 1, 2, or 3 years for firms that received their initial formal funding sooner rather than later, although notably to keep the variable count to minimum, the year variable was not implemented as a dummy, which would have been possibly able to convey more precise patterns of time.

5. Cross-validation interview results

Overall, the results from the cross-validation interview process are underlining the robustness of the results from the quantitative analysis, however, there are notable findings beyond just the validation of the results. The interviews also help to establish context and explain the findings. For the full interview guide and the summary of the results please refer to 'Appendix O' and for the interviewees' profile please refer to 'Appendix N'. The interview structure is similar to the results of quantitative analysis for improved comparability. However, starting with the most consequential validation, which in this case is the three-year interval. Although not central to the interview process it also aided in the validation of the investment cycle assumption the time frame based on. The aforementioned investment cycle of 18–24-month target in early-stage fintech startups was confirmed by both the investor and investee side expert.

When it comes to the validation of the quantitative results with a three-year time window by the investor and investee side expert the results overall are strong. However, the overlap of results is not exhaustive. First, looking at the finding that organizations that raised funds more slowly initially were less likely to secure subsequent funds successfully within three years, the investor side expert was in complete agreement whilst the investee side expert showed uncertainty.

"It's rather intuitive because unfortunately the VC industry is operating on 'FOMO' and many rounds get preempted, especially when there are good founders and they have good products, so typically good teams and products and vision will get funded or even preempted sooner than later, but it also displays the capability of founders to be able to fundraise. The time lag between the foundation of the firm and the initial investment is a sign of the quality of the team or the product which then makes it more likely that the venture is going to be able to raise funds within the target window."

-Investor side expert Rode (2024)

This suggests that the finding is valid. However, the cause of the relationship is due to the inherent qualities of the firm rather than a direct causal relationship of the time lag of the initial investment and the subsequent investment. As alluded to above, the investee side expert (Aziz, 2024) was less certain of the finding claiming that the causes of the time lag vary on a case-by-case basis and that there is no clear causality. Presented with the second finding of the quantitative analysis, the interview subjects showed agreement that startups headquartered in the capital of their country are more likely to raise funds within three years. However, both experts (Aziz, 2024, Rode, 2024) claimed that the effect may be caused by the concentration of talent and investors in the capitals of Germany, Austria and Switzerland. However, the investee side expert pointed out that for some business models within fintech it can be beneficial to be in the proximity of legislative bodies making it able to anticipate and respond to relevant legislative changes faster. Considering the findings if the coefficient associated with the CEO's education, the interviewees in accordance with each other stated that the findings did not fully match their expectations. Particularly, the fact both a completed bachelor's education and a doctorate were found to have a positive effect on the likelihood of subsequent investment within a three-year period whilst the completion of a master's degree was not (Aziz, 2024, Rode, 2024). However, the investee side expert pointed out that a bachelor's education is a basic pre-requisite in many cases whilst a research focused degree can be helpful when it comes to select industry niches where specific experience can be valuable (Aziz, 2024). None of the two interviewees were able to indicate causality. However, when it comes to the vertical specific findings with regards to the fundraising ability both the investor and investee side expert underlined the results of the quantitative analysis. Referring to the finding that SaaS focused DACH-based fintech startups are more likely to raise funds subsequent to their initial fundraising within a three-year period the investee side expert stated the following:

“It is generally very hard to raise in crypto because of the volatility of the market. It is frustrating to see that investors that are supposedly focusing on investing in risky early-stage ventures are more risk-averse than they ‘should’ be. Added to this, the option of ICOs is also preventing some startups from even seeking traditional external funding from VCs.”

-Investee side expert, Aziz (2024)

The sentiment is echoed by the investor side expert:

“ [The finding] is accurate. I think a lot of fintech startups in the crypto space go down the ICO route, it's just a way more lucrative for them to be honest.”

-Investor side expert, Rode (2024)

The finding from the quantitative analysis with regards to SaaS focused fintechs was also confirmed by both interviewees claiming that investors are generally attracted to business models with relatively stable recurring revenue streams. This makes the aforementioned firms more likely to be subsequently invested in (Aziz, 2024, Rode, 2024). When it comes to the finding that accelerators are negatively predictive of subsequent funding within three years, Rode (2024) expressed uncertainty with regard to the finding and claimed that accelerators encompass a wide range of programs and investors with a lot of variances in terms. However, the interviewee (Rode, 2024) also pointed out that promising teams of early ventures are able to avoid accelerators by using bootstrapped financing methods. The investee side expert (Aziz, 2024) was in concord with the statistical finding, stating that partaking in accelerator programs may actively hinder the subsequent fundraising ability of the firm due to early loss of equity.

All other statistically significant findings were discussed with the interviewees. However, due to the lower relevance with regard to the research questions and hypotheses compared to the three-year time window only deviations (non-validation) are elaborated upon with regard to the quantitative results from the one- and two-year time window results. When validating the two-year timeframe results, the finding was discussed that a higher number of initial investors is positively related to the likelihood of subsequent funding within two years. Although the investee side expert (Aziz, 2024) was in accordance with the finding, the investor side interviewee claimed that in his experience there was no clear evidence that this was the case, since many investors are very passive and add little additional value to subsequent fundraising or strategic advice (Rode, 2024). A further quantitative finding with only partial validation from the interviewees is that startups in the initial development phase (and not yet generating revenue) are more likely to receive subsequent funding within two years. Aziz (2024) claims that investors are likely to be drawn to prospective investments that started generating revenue earlier rather than later and thus the finding is not in accordance with his experience. Looking at the statistical findings using the one-year time frame, the validation interviews showed less conformity with the two- and three-year findings. The finding that a higher number of initial investors is positively related to the likelihood of subsequent funding within one year was confirmed again by Aziz (2024). It is, as in the case of the one-year time frame, not a relevant factor with regard to fundraising success according to Rode (2024). When it comes to the finding that startups that disclose their employee numbers publicly are more likely to raise funds within one year, both interviewees expressed uncertainty and disagreement (Aziz, 2024, Rode, 2024), claiming that the factor is not reflective of their experience. The same uncertainty was expressed when it came to the finding that fintech startups in the technology, media, and telecom (TMT) sectors are more likely to raise funds within one year.

"Interesting finding. Difficult to say. I am not sure what may be causing this."

-Investee side expert, Aziz (2024)

However, the statistical result that startups receiving early-stage venture capital investment as their first formal investment are less likely to raise funds within one year. Those receiving grants are more likely to raise funds within one year of the initial deal, was echoed by both interview subjects (Aziz, 2024, Rode, 2024). Notably, Aziz (2024) suggested that the firms seeking their first funding at a comparatively late stage were likely able to utilize bootstrapped financing methods and are entering a stage where external investment can be used to accelerate growth.

6. Discussion of the results and implications

The objective of this section is to answer the research questions and evaluate the previously formulated hypotheses connected with the research questions. Note that as previously mentioned, the questions and hypotheses considering the *ability* of the startup to raise funds subsequent to its initial deal, are evaluated using the results in a three-year time window. Where possible, the findings are compared with existent literature.

First with regards to the first research question ('**RQ1**'), posited as '*How do factors emergent in the initial fundraising process impact the subsequent fundraising ability of DACH-based early-stage fintech startups?',* it was observed that shorter time between the foundation of the firm was associated with an improved ability to raise funds. The finding was confirmed by Rode (2024). The finding enables the conclusive confirmation of hypothesis '**H1c**'; *"An increase in the time between the foundation date of the DACH-based fintech startups and their initial fundraising date negatively affects their subsequent fundraising ability".* Although the specific finding is not echoed by pre-existing research the importance of the time lag to the first investment was also found to be significant by Ünal (2019), suggesting that the finding prevails in geographic and industry agnostic samples.

Additionally, when it comes to factors emergent in the initial fundraising process, hypothesis '**H1d**'; "*The type of the initial deal of the DACH-based fintech startups affects their subsequent fundraising ability*" was confirmed by the statistical finding that accelerators as an initial investment type are negatively predictive of subsequent fundraising ability, with however no other types being statistically significant. The finding was validated by investee side expert Aziz (2024). The finding is contrary to research (Dams et al., 2016) arguing that accelerators lead an increased likelihood of VC funding subsequently. Notably, the compared research is industry and geography agnostic which can be the underlying cause of the discrepancy.

When it comes to '**H1a**' ("*The initial funding deal size has a positive impact on the subsequent fundraising ability of DACH-based fintech startups"*) and '**H1b**' ("*The number of investors involved in the initial deal has a positive impact on the subsequent fundraising ability of DACH-based fintech startups"*), neither could be confirmed. The result is partially due to the fact that, as mentioned before, the fundraising *ability* of the fintech firms is evaluated using the three-year time frame. Even though funding size and the number of investors involved in the previous deals have been shown to be predictive of startup success (Shah et al., 2023), the finding is not transferrable to the fundraising ability of DACH-based early-stage fintech startups. The result suggests that although not all factors emergent in the initial investment process affect the subsequent fundraising ability of DACH-based early-stage fintech startups, the time to the initial deal and the initial funding type both have an impact on the subsequent fundraising ability of the firms.

Next, focusing on the second research question ('**RQ2**'), posited as "*How do publicly available descriptive factors impact the subsequent fundraising ability of the DACH-based early stage fintech startups",* we observe significant findings. Pertaining to the formulated hypotheses, we can confirm '**H2a**' (*"The vector of the DACH-based fintech startups impacts their subsequent fundraising ability"*). Both the statistical analysis and the results from the interviews confirm the hypothesis, although with a minor caveat. Due to the suggestion of the literature and the interview responses from both Aziz (2024) and Rode (2024) it is unclear whether the in the case of crypto startups the statistical findings may be capturing effect different from true fundraising *ability*, since the sample does not include or account for ICOs. Thus, in the particular case of crypto startups, the finding is not conclusive, however, this is a special case. The aforementioned hypothesis can nonetheless be conclusively confirmed on the basis of the findings related to SaaS focused firms, where the finding of improved fundraising ability was confirmed by both the quantitative and qualitative analysis. This means that the vertical of the DACH-based early-stage fintech startups does play a role in their fundraising ability. The sentiment, that fintech startups differ in their fundraising patterns by sub-segments/vectors is echoed by Khajehpour, Mahdi and Yousefi Zenouz (2020). However, the specific finding with regards to fundraising *ability* of DACH-based early-stage fintech startups is novel. Notably, the finding of Zhyber et al. (2021) that B2B firms are more likely to garner funds was not reproduced. The second hypothesis connected to the aforementioned research question is '**H2b**', posited as "*The location of DACH-based fintech startups has an impact on their subsequent fundraising ability*". The hypothesis can be confirmed. It is clear that it is a positive predictor whether or not the firm is headquartered in the capital city of the country, however, the reason for the effect is not conclusively determinable, although based on the validation interviews it could be due to the available financial and human resources more readily available in the capitals. Third, we also confirm '**H2c**' (*"The level of education of the CEOs of the DACH-based fintech startups has an impact on their subsequent fundraising ability"*). Specifically, it can be concluded from both the quantitative and qualitative analysis that the level of education plays a role in the fundraising *ability* of the firm. Both having a bachelor's degree or PhD being positively predictive of fundraising *ability* according to the quantitative analysis. However, the specific effects were not validated by the interviews (Aziz, 2024; Rode, 2024) in the qualitative analysis. Again, due to the specific nature of the focus of the study, no equitable research exists. However, firms led by CEOs with PhDs have been shown to outperform their peers (Urquhart and Zhang, 2021) and similarly to the results of the present study, a completed MBA or the CEO having studied at a top university were not predictive of startup success (Eisenmann, 2020). However, again the investigated outcome and the sample of the compared literature is different from that of the present study, making the comparison not entirely applicable or directly comparable.

The third and final research question ('**RQ3**') is posited as "*Do different factors influence subsequent fundraising of the DACH-based early stage fintech startup when examining different time windows?*". Connected with the research question hypothesis '**H3**' is formulated as "*There are differences between the factors affecting subsequent fundraising of DACH-based fintech startups across time windows"* The hypothesis can be conclusively confirmed based on both statistical evidence and qualitative assessment. It is clear that there are factors predicting the fundraising of startups within one- and two-year timeframes which are not in line with the predictors within three-years which as mentioned before is treated as the 'fundraising *ability*' indicator. Again, directly comparable findings are currently non-existent. However, this observation can partially be caused by similar factors observed by Khajehpour, Mahdi and Yousefi Zenouz (2020) which suggests that different fintech startups have varying need for need for financing based on business model. However, the same sequential pattern conclusion cannot be drawn from the aforementioned result pertaining to '**RQ3**'.

The implications of the study are twofold. First, it provides factors that can be evaluated by prospective investors of DACH-based early-stage fintech startups that are predictive of subsequent fundraising success across three time windows. This is done with freely accessible factors which can be evaluated at minimal cost without having to conduct a costly due diligence process. Funding prediction, in its own right, is a two-sided issue. The occurrence of a subsequent funding indicates that the company is developing and attracting investor interest. Especially in the case of early-stage startups (depending on and specific stage of lifecycle of the firm) this can be an indication of the survival of the (startup) valley of death. However, from the perspective of the initial equity investment, it also causes dilution of the shares. It is thus important for investors to understand the factors that influence subsequent fundraising *ability* and subsequent fundraising across multiple time windows.

On the other hand, there are also implications for prospective and current DACH-based fintech founders. Understanding the impact of the examined factors can help founders better prepare for their initial fundraising by focusing on factors that impact their subsequent likelihood to be able to raise funds. These factors include lowering the time to their first investment, making consideration with regards to the type of the initial deal, taking educational background into consideration in, and importantly, focus on the verticals positively predictive and avoiding those negatively predictive of funding success. By doing so, founders can improve their startup's attractiveness to investors and improve their chances of securing the necessary funds subsequent to the initial fundraise.

7. Limitations and further research

The present research comes with multiple inherent limitations. First, although the findings are consequential and serve a twofold purpose as mentioned before, the generalizability of the findings is very limited since the scope is limited. Due to the sample used and the profile of the interviewees, the findings remain limited to early-stage DACH-based fintech firms, which make up a small fraction of all startups seeking funding globally. The sample is additionally biased, since only those firms appear in the data that have already received funding in the past. Although this is accounted for and highlighted in both the research questions and the hypotheses, it is a notable limitation of the research causing further decrease in generalizability.

Second, a key assumption lies at the root of the research. The thesis assumes that DACH-based early-stage fintech startups are intending to raise non-debt funds within a maximum of three years within the initial fundraiser. Although the assumption is in concord with public sentiment (Schulz, 2024, Cremades, 2019) and was cross validated by interview subjects Aziz (2024) and Rode (2024), the assumption does not necessarily hold true for every startup in the examined industry. There may be additional factors influencing the intention such as early profitability or a longer than expected financial runway causing the startup to raise funds later or self-finance altogether.

Although the results of the research were achieved through a mixed methods approach of implementing both quantitative and qualitative methods, it is difficult to establish conclusive causality between the observed effects and the outcome variables. The effects might be capturing inherent qualities of the firms rather than strictly the isolated effect of the given variable. This limitation is further exacerbated by the limited directly comparable literature in existence. It is also important to mention that the explanatory power observed in all models suggests that there are factors not included in the model that could further explain fundraising success.

In order to combat the limitations of the present study and expand the state of the knowledge in the field, further research should be conducted. Specifically, factors affecting funding success in startups within a specified timeframe is under-researched. This causes an issue, since there is significant utility in examining these factors for both prospective investors and investees beyond just the sheer occurrence of an investment in the future as was stipulated before in the thesis. These effects should also be studied in a wider range of samples or even completely geography and sector agnostically, like it has been done for general startup survival or success prediction based on various measured outcomes (Eisenmann, 2020; Ünal, 2019). Although a broader scope would be beneficial to establish a comparative baseline in the literature, it is also important to gain a further nuanced perspective on the sub-segment specific effects of the variables. This issue was clearly highlighted in the case of the finding of lower subsequent formal funding 'ability' of the crypto startups, which although statistically is a valid finding, the causality cannot be established due to an apparent bias in the funding mechanisms of crypto-focused fintech startups. The aforementioned observation also serves an example of why there is a need for further research in the area. Lastly, although the adjacent literature focuses on descriptive and highly accessible factors (as does the present thesis) it is also important to understand how more nuanced and less accessible factors affect the fundraising ability and more broadly the fundraising pattern of (fintech) startups. These factors include startup financials, more nuanced team composition, firm strategy, and market positioning.

8. Concluding remarks

The present study was aimed to understand the factors influencing the subsequent fundraising ability of early-stage fintech startups in the DACH region by employing both quantitative and qualitative methods. The thesis investigated factors that can be accessed with minimal cost or are emergent in the initial investment process. The research focused on three distinct time-windows for evaluating the subsequent funding occurrence: one year, two years, and three years post initial fundraising. The three-year timeframe was viewed as the most consequential one based on the general target fundraising cycle of early-stage startups.

The findings associated with the investment process include several factors that are observed to be influential. Firstly, a shorter time to secure initial funding is associated with a higher likelihood of subsequent funding. Secondly, the type of the initial completed deal matters. startups that initially raised funds through accelerators or incubators are less likely to secure further investment within three years of the initial investment.

As demonstrated by the results of the study, publicly available descriptive factors also play a significant role. Sector-specific effects show that SaaS-focused fintech startups have a higher likelihood of securing subsequent funding, while being headquartered in capital cities enhances fundraising success due to the concentration of resources. Additionally, the educational background of the CEO is important, with startups led by CEOs with a bachelor's degree or a doctorate being more likely to secure additional funding.

Notably, these factors were not consistent when viewing the results from the one- and two-year timeframes. This suggests that different factors are predictive of funding success (or intent in the case of the one-year time window) compared to the three-year results which was used as a proxy for investigating funding ability.

For investors, understanding these factors can streamline due diligence and identify promising investment opportunities, whilst incurring minimal cost. For founders and executives of DACH-based early-stage fintech startups, these insights can guide strategic decisions when it comes to decisions concerning the choice of verticals, the top executive of the firm and the initial formal funding process to improve their startup's attractiveness to prospective investors.

Despite the robustness of the findings, the scope is limited to early-stage fintech startups in the DACH-region, and the assumption that all startups within the field and stage aim to raise non-debt funds within three years may not hold universally.

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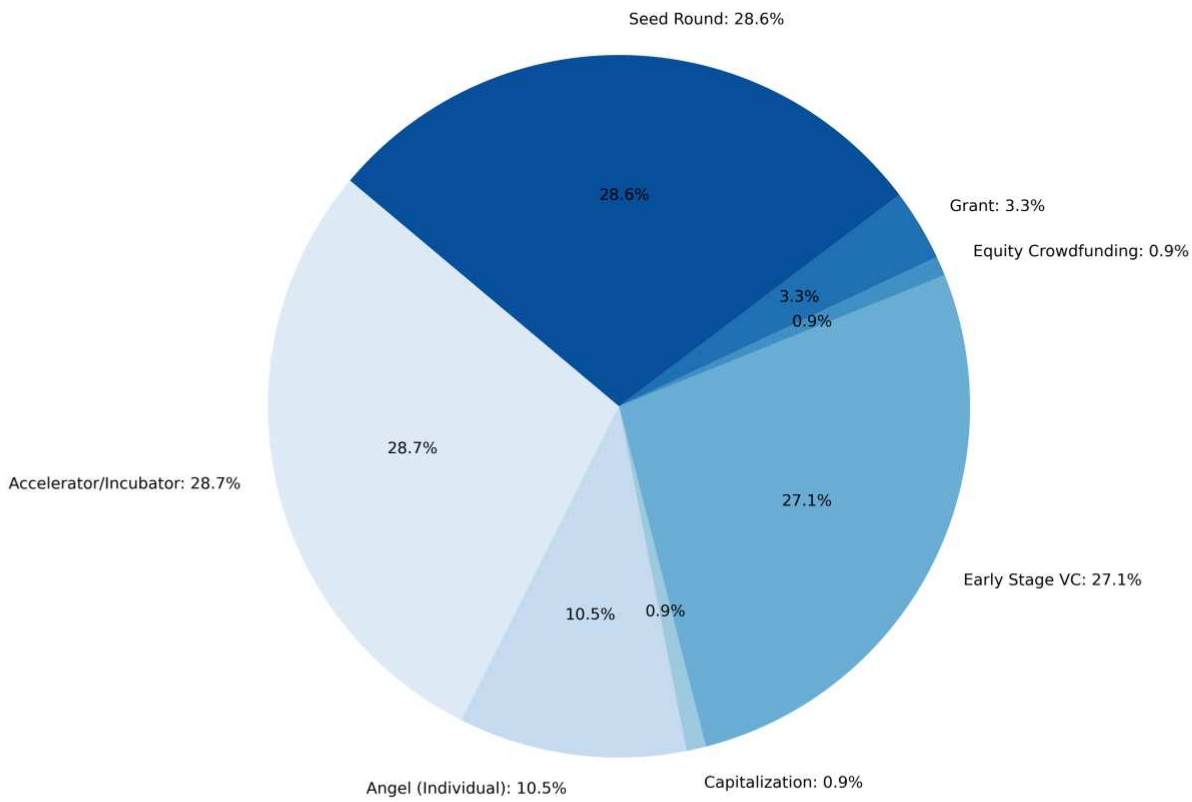
10. Appendix A: Summary statistics of final dataset

variable	*definition*	*count*	*mean*	*std*	*min*	*25%*	*50%*	*75%*	*max*
business_status_generating revenue_binary	Whether business is listed as generating revenue (1 if yes, 0 otherwise)	543.000	0.536	0.499	0.000	0.000	1.000	1.000	1.000
business_status_product development_binary	Whether business is listed as being in the product development phase (1 if yes, 0 otherwise)	543.000	0.006	0.074	0.000	0.000	0.000	0.000	1.000
business_status_product in beta test_binary	Whether business is listed as being in product beta testing phase (1 if yes, 0 otherwise)	543.000	0.013	0.113	0.000	0.000	0.000	0.000	1.000
business_status_profitable_binary	Whether business is listed as being profitable (1 if yes, 0 otherwise)	543.000	0.006	0.074	0.000	0.000	0.000	0.000	1.000
business_status_startup_binary	Whether business is listed as being in 'startup' phase (1 if yes, 0 otherwise)	543.000	0.438	0.497	0.000	0.000	0.000	1.000	1.000
business_status_stealth_binary	Whether business is listed as being in 'stealth' mode (1 if yes, 0 otherwise)	543.000	0.002	0.043	0.000	0.000	0.000	0.000	1.000
ceo_educ_bachelor_binary	Whether CEO has a bachelors degree (1 if yes, 0 otherwise)	543.000	0.611	0.466	0.000	0.000	0.000	1.000	1.000
ceo_educ_doctorate_binary	Whether CEO has a doctorate (1 if yes, 0	543.000	0.158	0.311	0.000	0.000	0.000	0.000	1.000
ceo_educ_ivy_binary	Whether CEO graduated from ivy league school (1 if yes, 0 otherwise)	543.000	0.055	0.159	0.000	0.000	0.000	0.000	1.000
ceo_educ_listed_binary	Whether CEO's education is listed (1 if yes, 0 otherwise)	543.000	0.878	0.492	0.000	0.000	1.000	1.000	1.000
ceo_educ_mba_ma_binary	Whether CEO has a masters or MBA degree (1 if yes, 0 otherwise)	543.000	0.420	0.467	0.000	0.000	0.000	1.000	1.000
deal_size_imputed	Deal size of initial fundraiser in millions of €	543.000	4.620	9.710	0.011	0.536	4.423	4.891	187.311
deal_type_accelerator/incubator_binary	Whether deal type of initial deal was accelerator/incubator (1 if yes, 0 otherwise)	543.000	0.287	0.453	0.000	0.000	0.000	1.000	1.000
deal_type_angel (individual)_binary	Whether deal type of initial deal was angel investment (1 if yes, 0 otherwise)	543.000	0.105	0.307	0.000	0.000	0.000	0.000	1.000
deal_type_capitalization_binary	Whether deal type of initial deal was 'capitalization' (1 if yes, 0 otherwise)	543.000	0.009	0.096	0.000	0.000	0.000	0.000	1.000
deal_type_early stage vc_binary	Whether deal type of initial deal was early stage venture capital invetsment (1 if yes, 0 otherwise)	543.000	0.271	0.445	0.000	0.000	0.000	1.000	1.000
deal_type_equity crowdfunding_binary	Whether deal type of initial deal was equity crowdfunding (1 if yes, 0 otherwise)	543.000	0.009	0.096	0.000	0.000	0.000	0.000	1.000
deal_type_grant_binary	Whether deal type of initial deal was grant (1 if yes, 0 otherwise)	543.000	0.033	0.179	0.000	0.000	0.000	0.000	1.000
deal_type_seed round_binary	Whether deal type of initial deal was seed round investment (1 if yes, 0 otherwise)	543.000	0.286	0.438	0.000	0.000	0.000	1.000	1.000
dependent_var_1_year	Whether company closed successful fundraiser within 1 year from initial fundraising date (1 if yes, 0 otherwise)	543.000	0.260	0.439	0.000	0.000	0.000	1.000	1.000
dependent_var_2_years	Whether company closed successful fundraiser within 2 years from initial fundraising date (1 if yes, 0 otherwise)	543.000	0.505	0.500	0.000	0.000	1.000	1.000	1.000
dependent_var_3_years	Whether company closed successful fundraiser within 3 years from initial fundraising date (1 if yes, 0 otherwise)	543.000	0.613	0.487	0.000	0.000	1.000	1.000	1.000
employees_given_binary	Whether employees are given (1 if yes, 0	543.000	0.077	0.267	0.000	0.000	0.000	0.000	1.000
fed_rate	Effective federal funds rate on day of initial investment	543.000	0.917	0.826	0.040	0.130	0.550	1.565	2.450
founded_to_deal_time	Time from founding of firm to initial fundraiser	543.000	596.687	542.548	0.000	261.000	444.000	776.000	3927.000
hq_austria_binary	Whether the company is headquarted in Austria (1 if yes, 0 otherwise)	543.000	0.083	0.276	0.000	0.000	0.000	0.000	1.000
hq_capital_binary	Whether the company is headquarted in a capital city (1 if yes, 0 otherwise)	543.000	0.319	0.466	0.000	0.000	0.000	1.000	1.000
hq_germany_binary	Whether the company is headquarted in Germany (1 if yes, 0 otherwise)	543.000	0.532	0.499	0.000	0.000	1.000	1.000	1.000
hq_switzerland_binary	Whether the company is headquarted in Germany (1 if yes, 0 otherwise)	543.000	0.385	0.487	0.000	0.000	0.000	1.000	1.000
log_deal_size_imputed	log base 10 transformed version of deal size of initial fundraiser	543.000	0.463	1.953	-4.556	-0.625	1.487	1.587	5.233
log_founded_to_deal_time	log base 10 transformed version of Time from founding of firm to initial fundraiser	543.000	5.020	4.062	-9.210	5.565	6.096	6.654	8.276
log_n_investors_adjusted	log base 10 transformed version of The number of investors investing during the first deal	543.000	0.451	0.694	0.000	0.000	0.000	0.693	3.738
n_investors_adjusted	The number of investors investing during the first deal (if equity crowdfunding treated as =1)	543.000	2.197	2.932	1.000	1.000	1.000	2.000	42.000
relevant_yearly_gdp_growth_rate	Annual GDP growth rate of country of headquarters in year of initial fundraiser	543.000	0.009	0.020	-0.063	0.010	0.014	0.022	0.039
relevant_yearly_inflation_rate	Annual inflation rate of country of headquarters in year of initial fundraiser	543.000	0.008	0.009	-0.011	0.001	0.005	0.015	0.033
vertical_ai_binary	Whether company is focused on AI vector (1 if yes, 0 otherwise)	543.000	0.123	0.329	0.000	0.000	0.000	0.000	1.000
vertical_b2b_binary	Whether company is business customer oriented (1 if yes, 0 otherwise)	543.000	0.022	0.147	0.000	0.000	0.000	0.000	1.000
vertical_climate_binary	Whether company is focused on mobile vector (1 if yes, 0 otherwise)	543.000	0.018	0.135	0.000	0.000	0.000	0.000	1.000
vertical_crypto_binary	Whether company is focused on crypto vector (1 if yes, 0 otherwise)	543.000	0.252	0.435	0.000	0.000	0.000	1.000	1.000
vertical_mobile_binary	Whether company is focused on mobile vector (1 if yes, 0 otherwise)	543.000	0.171	0.377	0.000	0.000	0.000	0.000	1.000
vertical_saas_binary	Whether company is focused on SaaS vector (1 if yes, 0 otherwise)	543.000	0.254	0.436	0.000	0.000	0.000	1.000	1.000
vertical_tmt_binary	Whether company is focused on TMT vector (1 if yes, 0 otherwise)	543.000	0.298	0.458	0.000	0.000	0.000	1.000	1.000
year_only	Year of the initial investment	543.000	2015.785	2.517	2010.000	2014.000	2016.000	2018.000	2020.000

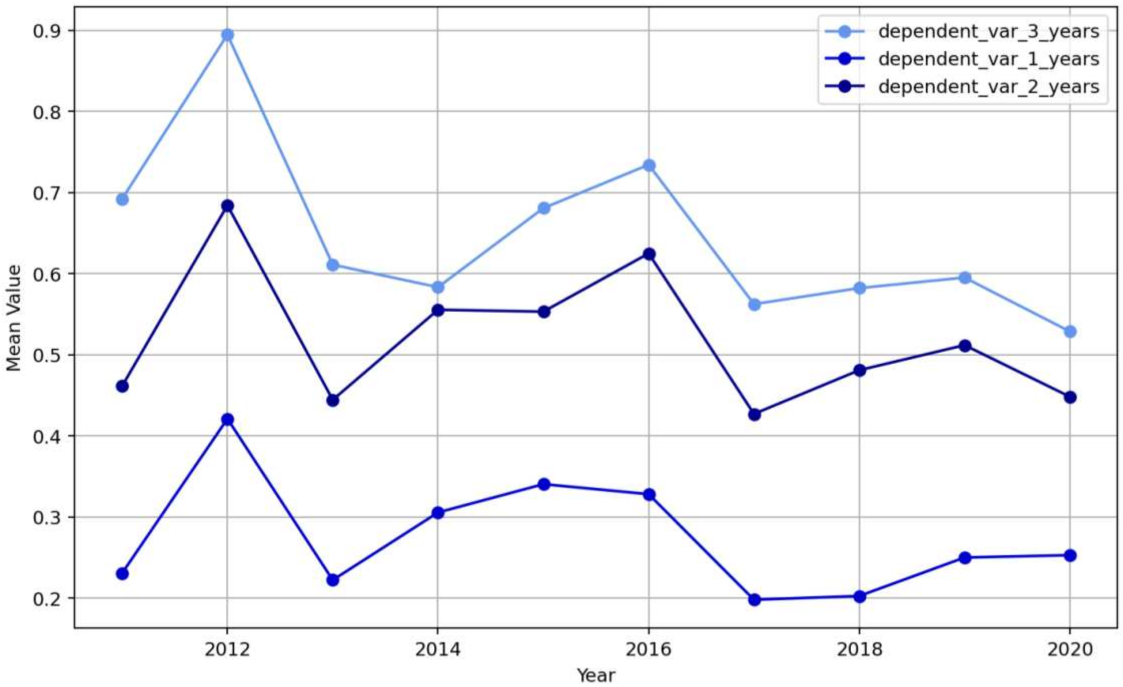
Source: Own representation

11. Appendix B: Pie chart of deal types in dataset



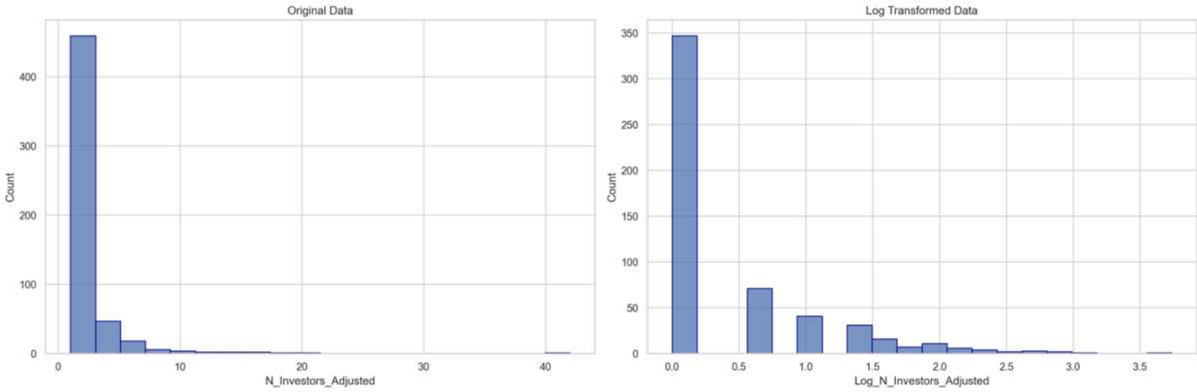
Source: Own graphical representation

12. Appendix C: Line plot of dependent variable means over time



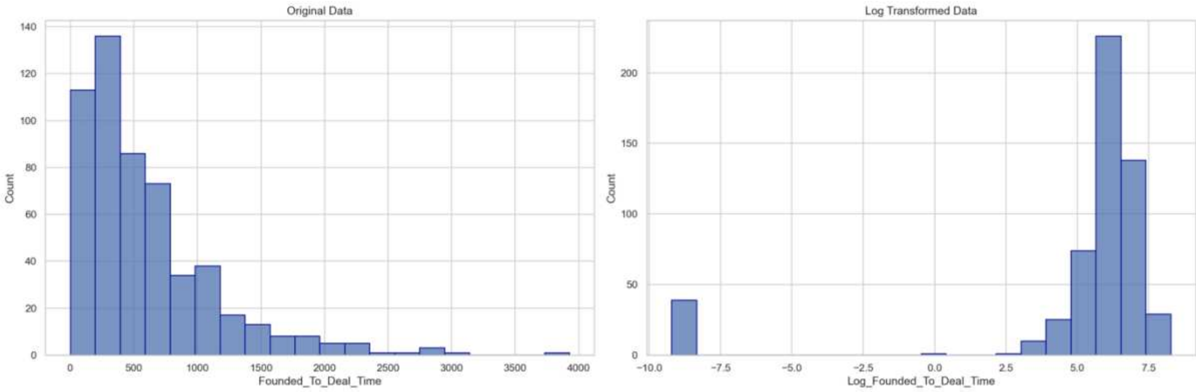
Source: Own graphical representation

13. Appendix D: Histogram for number of investors log transformation



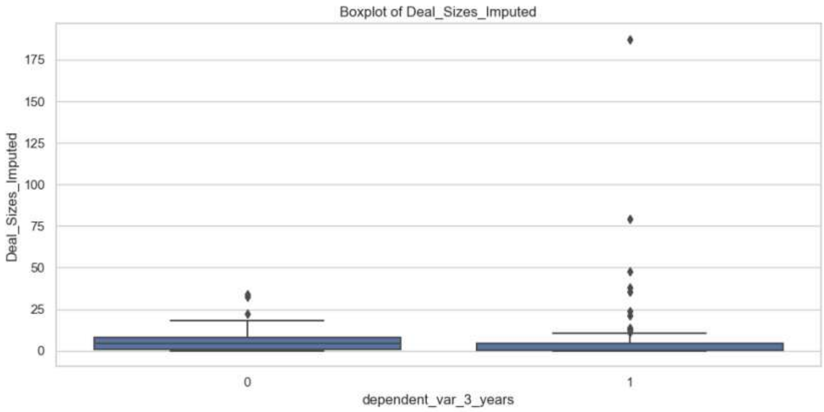
Source: Own graphical representation

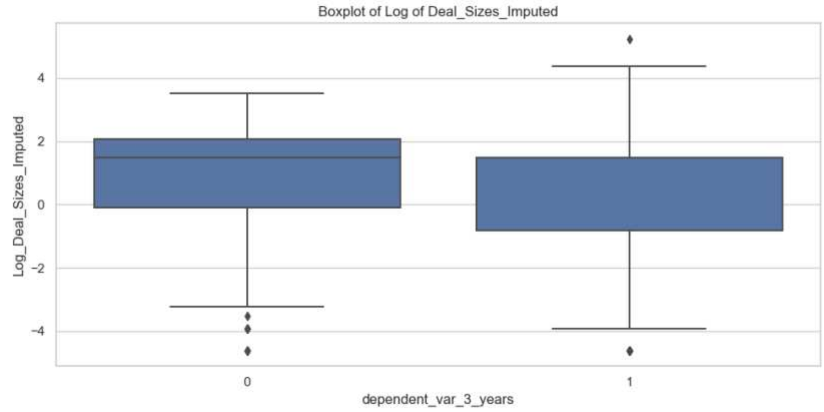
14. Appendix E: Histogram for founded to deal time log transformation

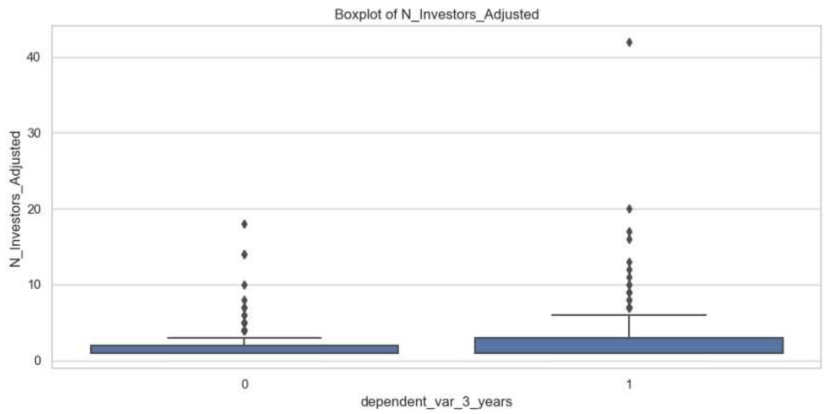


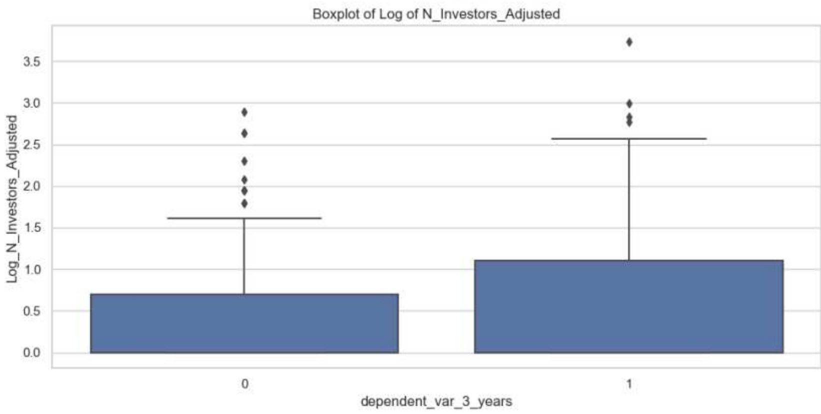
Source: Own graphical representation

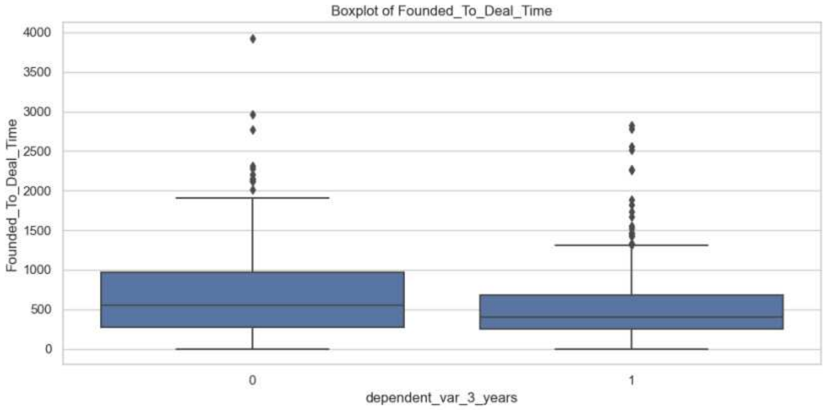
15. Appendix F: Boxplots of continuous variables by dependent variable

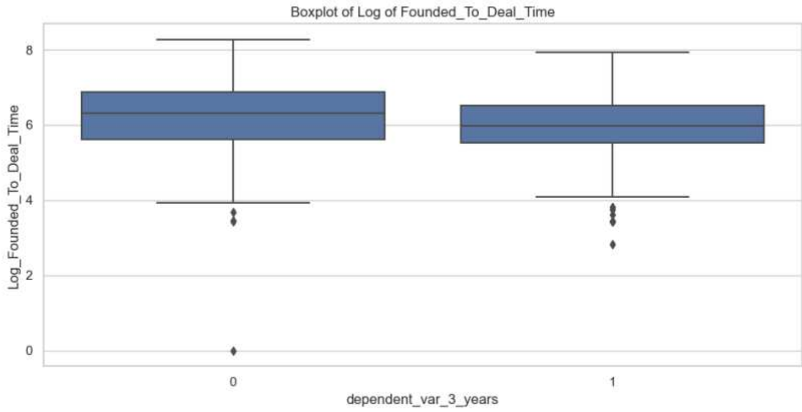


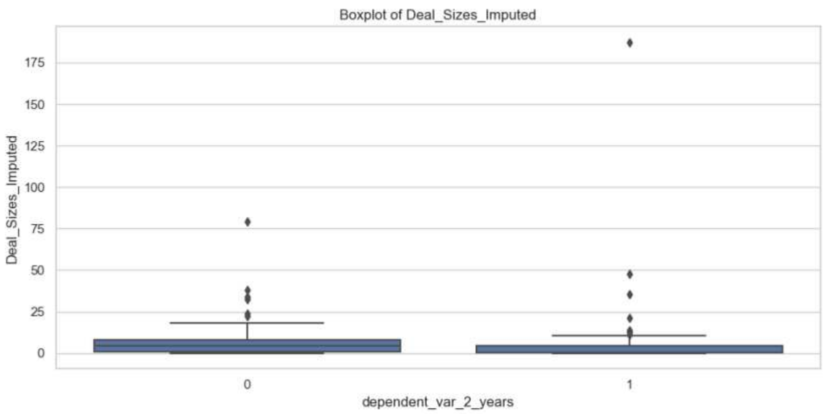


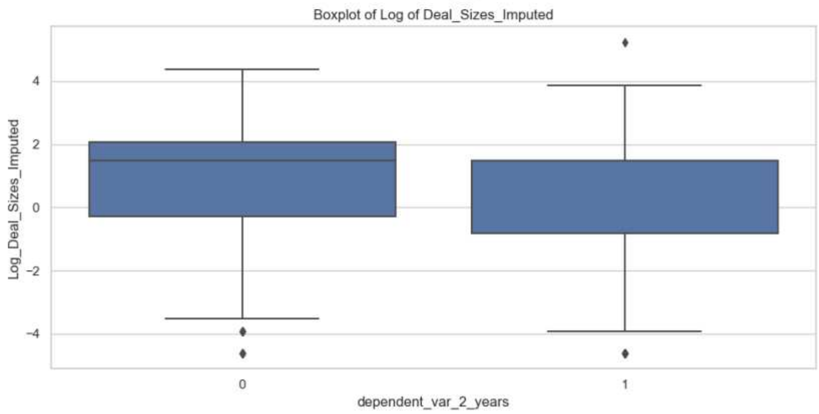


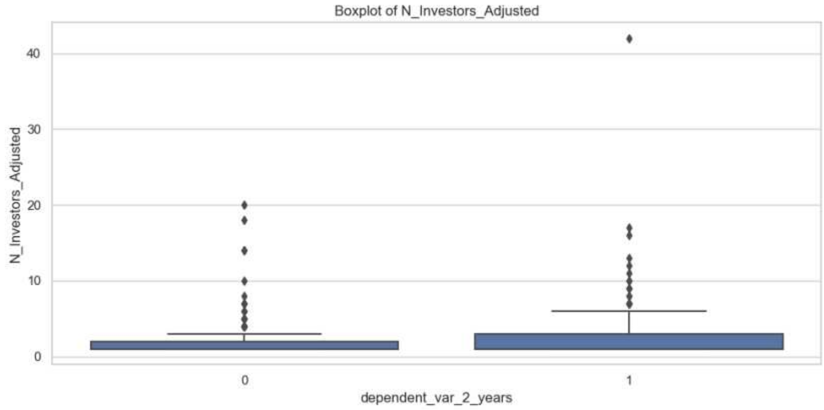


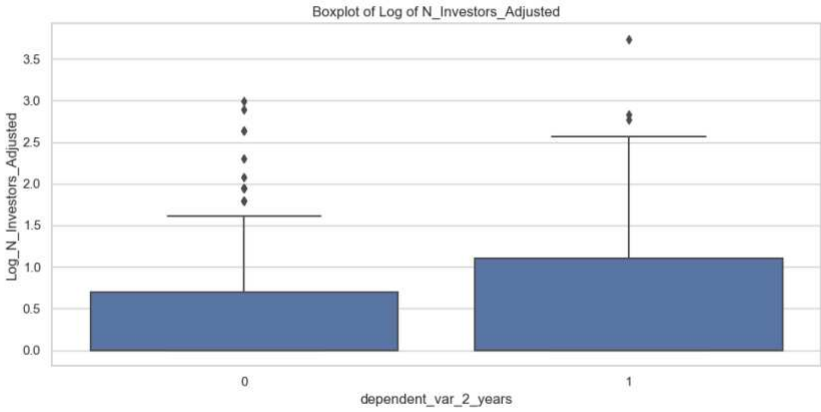

Boxplot of Founded_To_Deal_Time
Founded_To_Deal_Time
4000
3500
3000
2500
2000
1500
1000
500
0
0
1
dependent_var_3_years

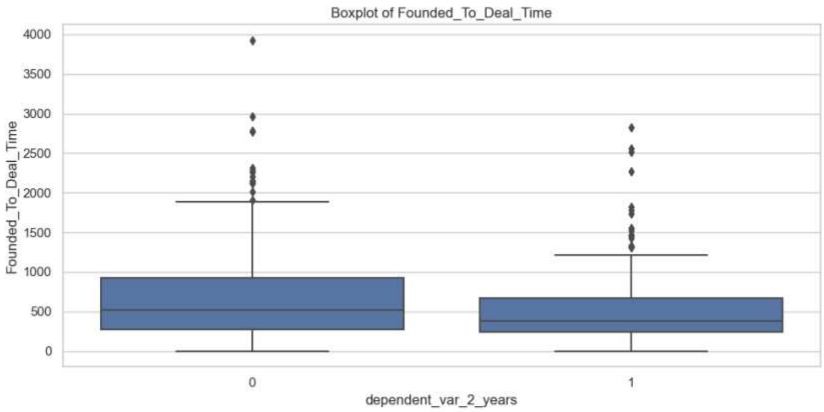

Boxplot of Log of Founded_To_Deal_Time
Log_Founded_To_Deal_Time
8
6
4
2
0
0
1
dependent_var_3_years

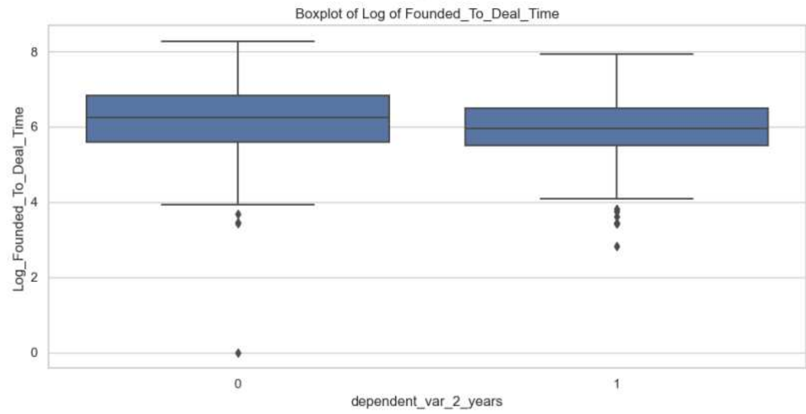

Boxplot of Deal_Sizes_Imputed
Deal_Sizes_Imputed
175
150
125
100
75
50
25
0
0
1
dependent_var_2_years

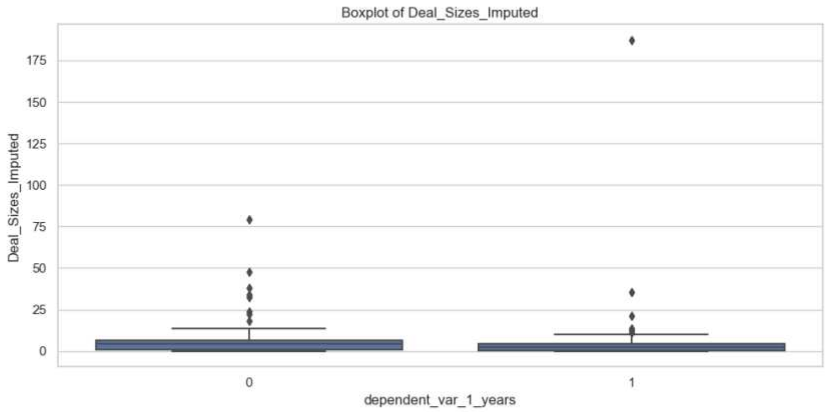

Boxplot of Log of Deal_Sizes_Imputed
Log_Deal_Sizes_Imputed
4
2
0
−2
−4
0
1
dependent_var_2_years

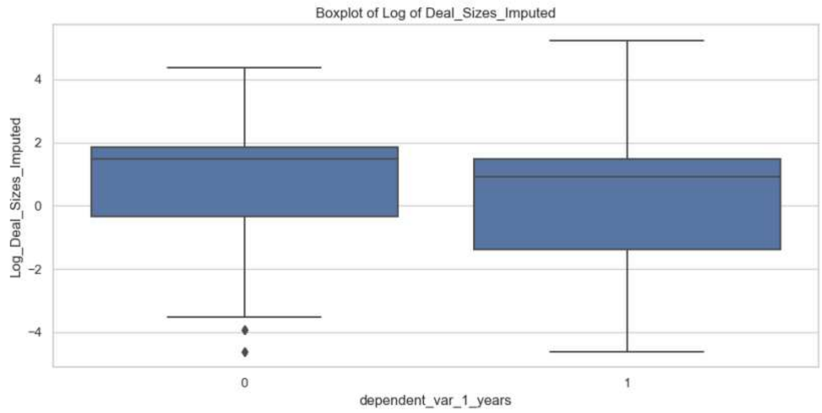

Boxplot of N_Investors_Adjusted
N_Investors_Adjusted
dependent_var_2_years
0
1
0
10
20
30
40

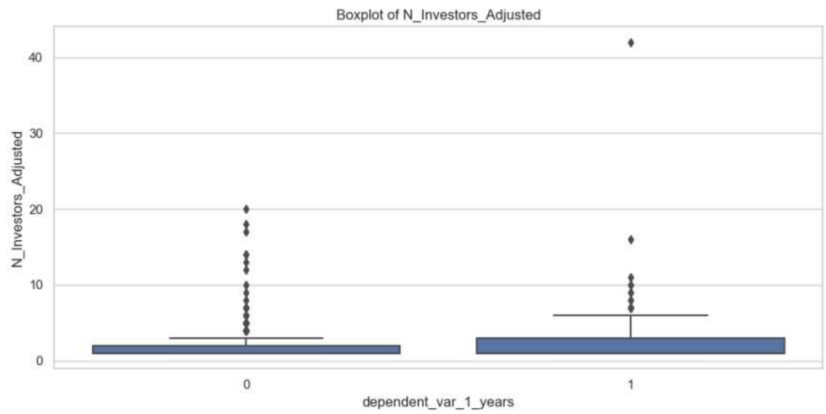

Boxplot of Log of N_Investors_Adjusted
Log_N_Investors_Adjusted
dependent_var_2_years
0
1
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5

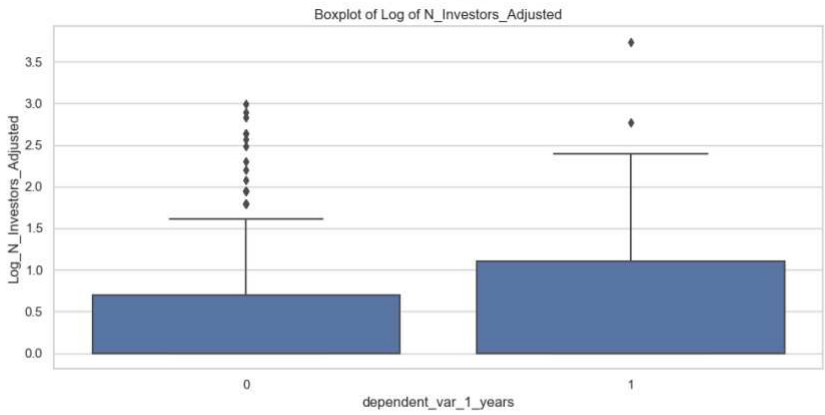

Boxplot of Founded_To_Deal_Time
Founded_To_Deal_Time
dependent_var_2_years
0
1
0
500
1000
1500
2000
2500
3000
3500
4000

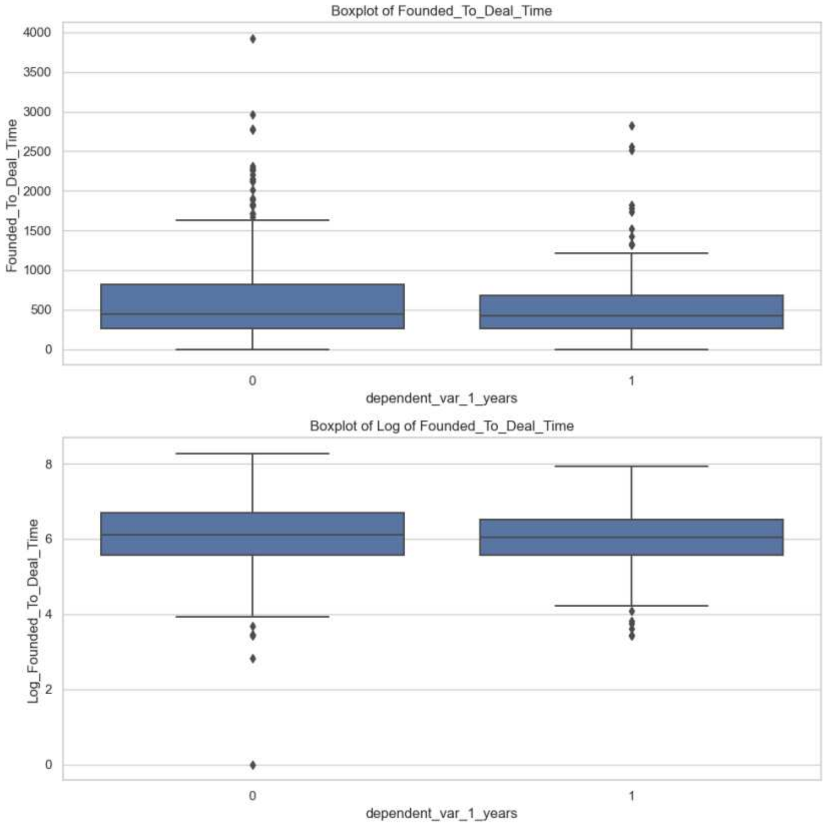

Boxplot of Log of Founded_To_Deal_Time
Log_Founded_To_Deal_Time
dependent_var_2_years
0
1
0
2
4
6
8


Boxplot of Deal_Sizes_Imputed
Deal_Sizes_Imputed
0
25
50
75
100
125
150
175
0
1
dependent_var_1_years


Boxplot of Log of Deal_Sizes_Imputed
Log_Deal_Sizes_Imputed
−4
−2
0
2
4
0
1
dependent_var_1_years

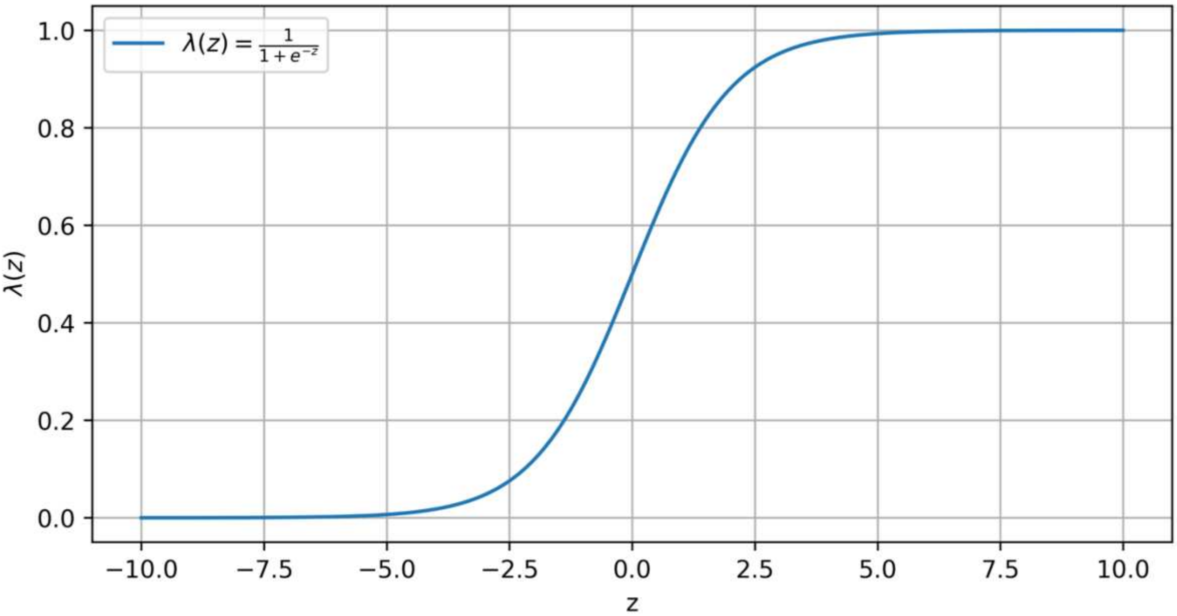

Boxplot of N_Investors_Adjusted
N_Investors_Adjusted
0
10
20
30
40
0
1
dependent_var_1_years


Boxplot of Log of N_Investors_Adjusted
Log_N_Investors_Adjusted
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0
1
dependent_var_1_years



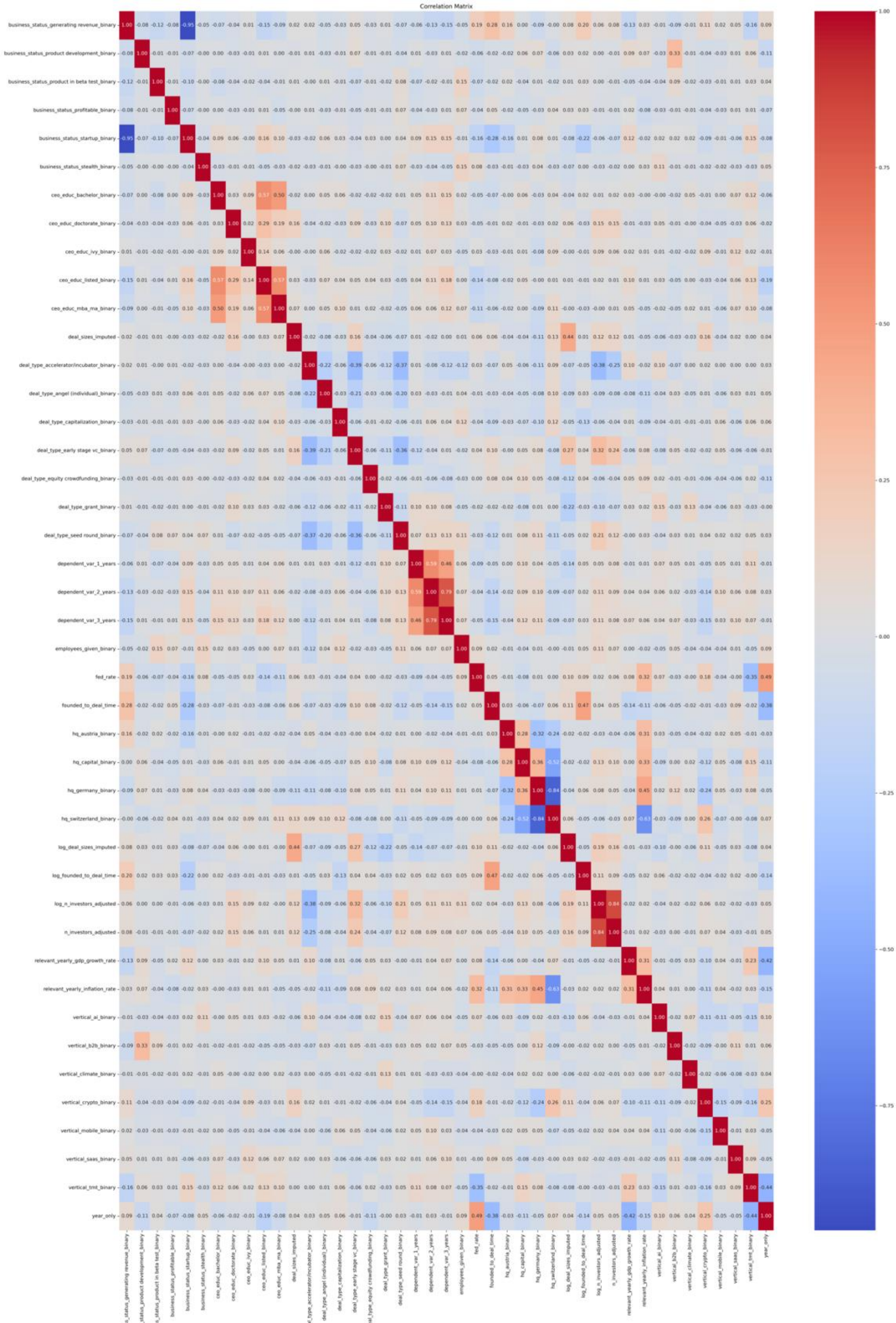
Source: Own graphical representation

16. Appendix G: Graphical representation of the sigmoid function



Source: Own graphical representation based on Hastie, T., Tibshirani, R. and Friedman, J. (2009). Springer Series in Statistics The Elements of Statistical Learning Data Mining, Inference, and Prediction Second Edition. [online] pp. 131-137. Available at: https://www.sas.upenn.edu/~fdiebold/NoHesitations/BookAdvanced.pdf.

17. Appendix H: Correlation matrix



Source: Own graphical representation, visualized in Python

18. Appendix I: Logistic regression output with all viable variables

variables	*(1a)* *dependent_var_1_years*	*(2a)* *dependent_var_2_years*	*(3a)* *dependent_var_3_years*
log_deal_sizes_imputed	-0.0927*	-0.0385	-0.0691
	(0.0555)	(0.0524)	(0.0549)
n_investors_adjusted	0.0881**	0.0645	0.0509
	(0.0421)	(0.0417)	(0.0442)
founded_to_deal_time	0.000349	-0.000106	-0.000234
	(0.000309)	(0.000274)	(0.000282)
hq_capital_binary	0.546*	0.317	0.652**
	(0.281)	(0.249)	(0.269)
hq_germany_binary	-0.347	0.235	0.0156
	(0.368)	(0.323)	(0.336)
hq_austria_binary	-0.572	-0.0185	-0.517
	(0.602)	(0.533)	(0.559)
hq_switzerland_binary	-	-	-
employees_given_binary	0.885**	0.553	0.624
	(0.408)	(0.390)	(0.424)
business_status_stealth_binary	-	-	-
business_status_startup_binary	0.213	0.456**	0.422*
	(0.232)	(0.207)	(0.217)
business_status_profitable_binary	-	-0.531	0.438
		(1.326)	(1.306)
business_status_productinbeta_binary	-	-0.396	-0.137
		(0.852)	(0.848)
business_status_productdevelopment_binary	0.199	-0.403	-0.336
	(1.501)	(1.362)	(1.451)
business_status_generatingreven	-	-	-
ceo_educ_ivy_binary	-0.115	0.867	0.104
	(0.664)	(0.647)	(0.659)
ceo_educ_bachelor_binary	-0.0111	0.320	0.393
	(0.292)	(0.261)	(0.279)
ceo_educ_doctorate_binary	0.144	0.524	0.850**
	(0.361)	(0.339)	(0.389)
ceo_educ_listed_binary	-0.0568	0.169	0.336
	(0.317)	(0.275)	(0.286)
ceo_educ_mba_ma_binary	0.273	-0.0923	0.0488
	(0.287)	(0.258)	(0.278)
vertical_ai_binary	0.570*	0.402	0.399
	(0.319)	(0.303)	(0.324)
vertical_b2b_binary	0.915	0.0483	0.877
	(0.771)	(0.706)	(0.881)
vertical_climate_binary	-0.164	-0.884	-1.008
	(0.756)	(0.710)	(0.711)
vertical_crypto_binary	-0.0969	-0.538**	-0.569**
	(0.277)	(0.241)	(0.243)
vertical_mobile_binary	0.417	0.494*	0.0602
	(0.279)	(0.258)	(0.269)
vertical_saas_binary	0.0233	0.277	0.537**
	(0.252)	(0.226)	(0.241)
vertical_tmt_binary	0.554**	0.265	0.00803
	(0.271)	(0.242)	(0.256)

deal_type_acceleratorincubator_binary	1.815*	-0.0694	-0.0251
	(1.102)	(0.656)	(0.647)
deal_type_angelindividual_binary	1.798	-0.143	0.187
	(1.126)	(0.697)	(0.689)
deal_type_capitalization_binary	0.664	1.055	0.969
	(1.606)	(1.333)	(1.344)
deal_type_earlystagevc_binary	1.007	-0.0700	0.343
	(1.096)	(0.646)	(0.637)
deal_type_equitycrowdfunding_binary	0.997	-1.292	-1.922
	(1.593)	(1.318)	(1.317)
deal_type_grant_binary	2.701**	1.407	1.390
	(1.207)	(0.885)	(0.925)
deal_type_seedround_binary	1.820*	0.524	0.830
	(1.099)	(0.659)	(0.655)
relevant_yearly_gdp_growth_rate	-2.795	6.589	7.785
	(7.563)	(6.759)	(7.196)
relevant_yearly_inflation_rate	22.21	-2.342	6.615
	(22.36)	(20.07)	(20.99)
year_only	0.109	0.115	0.0509
	(0.0897)	(0.0803)	(0.0844)
fed_rate	-0.378*	-0.107	-0.0711
	(0.228)	(0.199)	(0.206)
constant	-224.0	-232.5	-103.2
	(180.8)	(161.9)	(170.2)
Hosmer-Lemeshow test result	Prob > chi2 = 0.0575	Prob > chi2 = 0.1319	Prob > chi2 = 0.1190
McFadden's Pseudo R-squared value	0.094	0.1068	0.1353
Observations	543	543	543

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Own representation

19. Appendix J: Logistic regression link test results with all viable variables

dependent_var_1_year (1a)	*Coefficient*	*P>|z|*
Hat	1.319027	0.000
Hat squared	0.1731236	0.160
Constant	0.0566073	0.757

dependent_var_2_years (2a)	*Coefficient*	*P>|z|*
Hat	1.032959	0.000
Hat squared	-0.1149801	0.267
Constant	0.0636211	0.561

dependent_var_3_years (3a)	*Coefficient*	*P>|z|*
Hat	1.085817	0.000
Hat squared	-0.0847152	0.338
Constant	0.0393252	0.731

Source: own representation

20. Appendix K: Backwards elimination process

```python
import pandas as pd
import statsmodels.api as sm

# Step 1: Prepare the independent variables (X) and dependent variable (y)
X = df[independent_vars]
y = df[dependent_var]

# Step 2: Add a constant to the model to account for the intercept
X = sm.add_constant(X)

def backward_elimination(X, y, significance_level=0.05):
    # Step 3: Create a list of initial variables including the constant
    initial_vars = X.columns.tolist()

    while True:
        # Step 4: Fit the logistic regression model without displaying the output
        model = sm.Logit(y, X).fit(disp=0)

        # Step 5: Get the p-values for the predictors, excluding the intercept
        pvalues = model.pvalues.drop('const')

        # Step 6: Find the maximum p-value among the predictors
        max_pvalue = pvalues.max()

        # Step 7: Check if the maximum p-value exceeds the significance level
        if max_pvalue > significance_level:
            # Step 8: If it does, drop the predictor with the highest p-value
            excluded_var = pvalues.idxmax()
            X = X.drop(columns=[excluded_var])
            print(f"Dropped {excluded_var} with p-value {max_pvalue}")
        else:
            # Step 9: If no p-values exceed the significance level, stop the process
            break

    # Step 10: Return the final model
    return model

# Step 11: Run the backward elimination process
final_model = backward_elimination(X, y)

# Step 12: Print the summary of the final logistic regression model
print(final_model.summary())
```

Source: own representation, note that the code is partially LLM generated, implemented in Python

21. Appendix L: Logistic regression output with backwards selected variables

variables	(1b) dependent_var_1_years	(2b) dependent_var_2_years	(3b) dependent_var_3_years
log_deal_sizes_imputed	-0.139***		
	(0.0508)		
founded_to_deal_time			-0.000529***
			(0.000183)
n_investors_adjusted	0.0988***	0.0994**	
	(0.0370)	(0.0392)	
hq_capital_binary			0.492**
			(0.210)
business_status_startup_binary			0.434**
			(0.200)
ceo_educ_bachelor_binary		0.457**	0.602***
		(0.192)	(0.211)
ceo_educ_doctorate_binary			0.954***
			(0.349)
vertical_mobile_binary		0.498**	
		(0.242)	
vertical_crypto_binary		-0.567***	-0.574***
		(0.212)	(0.212)
vertical_tmt_binary	0.472**		
	(0.212)		
vertical_saas_binary			0.597***
			(0.227)
deal_type_earlystagevc_binary	-0.625**		
	(0.264)		
deal_type_acceleratorincubator_binary			-0.584***
			(0.206)
deal_type_grant_binary		1.457**	
		(0.584)	
Constant	-1.230***	-0.0450	0.365
	(0.154)	(0.174)	(0.233)
Hosmer-Lemeshow test result	Prob > chi2 = 0.1668	Prob > chi2 = 0.6212	Prob > chi2 = 0.3407
McFadden's Pseudo R-squared value	0.0436	0.0548	0.0958
Observations	543	543	543

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: own representation

22. Appendix M: Logistic regression link test results with backwards selected variables

dependent_var_1_year (1b)	*Coefficient*	*P>|z|*
Hat	1.620283	0.000
Hat squared	0.3202332	0.313
Constant	0.2198619	0.499

dependent_var_2_years (2b)	*Coefficient*	*P>|z|*
Hat	1.018868	0.000
Hat squared	-0.0768892	0.637
Constant	0.0220669	0.827

dependent_var_3_years (3b)	*Coefficient*	*P>|z|*
Hat	1.138943	0.000
Hat squared	-0.1417734	0.274
Constant	0.0399679	0.727

Source: own representation

23. Appendix N: Interview subject profiles

Investor side expert

Name: Bob Rode
LinedIn: https://www.linkedin.com/in/bobrode/
Current position: Partner at 6 Degrees Capital
Experience: Mr. Rode is an expert in early-stage startup investing with 5+ years of equity and non-equity investments. He is currently a principal at 6 Degrees Capital, focusing on seed and Series A investments in fintech and B2B SaaS. His expertise was honed during his tenure at Plug and Play Tech Center, where he served as EMEA IC & Director. In this role, he led the Frankfurt office, collaborated with financial institutions and large enterprises, and contributed to the investment committee for EMEA, crafting investment strategies and managing key financial stakeholder relationships. Mr. Rode's career has involved working with early-stage fintechs based in the DACH-region.

Investee side expert

Name: Mandya Aziz
LinedIn: https://www.linkedin.com/in/mandyaaziz/
Current position: Chief of Staff at Banxware
Experience: Mr. Aziz has substantial experience in the finech and consulting sectors, with a strong focus on startup ventures. At Banxware in Berlin, Germany, he has served as the Chief of Staff since December 2021 and previously as a Venture Architect from October 2020 to November 2021. In these roles, he was instrumental in leading three early-stage investment rounds, successfully securing over 20 million EUR in total funding. His prior roles include working as a Consultant at Berylls Strategy Advisors and engaging in Innovation Consulting at Deloitte.

24. Appendix O: Interview guide and summary of responses

Section	Guided Items	Investor Side Answers (Summary)	Investee Side Answers (Summary)
Introduction	The thesis is focusing on predictors of funding success of startups. In particular, we focus on funding that are accessible at minimal cost or are emergent in the funding process. Your insights will help validate and contextualize the findings from the quantitative analysis. Before we begin, *these (show table and explain)* are the investigated variables. First, we will focus on the startups *ability to raise funds* within the normal target timeframe of three years.	-	-
Startup Fundraising ability (Three-year timframe) validation	Finding 1: Organizations that raised funds more slowly initially were less likely to secure subsequent funds successfully within three years. Question: In your experience, is this the case and why might fintech startups that take longer to raise their initial funds struggle to secure additional funding within three years? Are there specific challenges these startups face that others do not?	*According to the interviewee, good teams with strong products and vision tend to get funded quickly, often preemptively. This demonstrates the founders' fundraising abilities and highlights that some are better at it than others. The interviewee agrees that this makes sense intuitively, since the industry is often 'FOMO' driven, with many investors wanting to get in on a startup when it seeks funds and the team is strong.*	*It depends on the model of the startup that works straight away and can bootstrap it without formal funding. Early revenue generation can delay the need for external investment. After public disclosure it gets faster, and founders are usually more willing to raise funds in order to accelerate the growth of the firm with external funding.*
	Finding 2: Startups headquartered in the capital of their country are more likely to raise funds within three years. Question: Do you think being headquartered in the capital city of a country influences a startup's ability to raise funds? Are there specific advantages or resources available in capital cities that might contribute to this trend?	*According to the interviewee, it is definitely the case; however, it is not clear whether the positive association is due to the closeness of the legislative bodies. For some verticals, this is important, but generally, it is more about the correlation of concentrated capital resources in the capital cities. The interviewee notes that it is something visible in practice, as successful fintech firms are often concentrated around the capitals.*	*The interviewee agrees, however, the only reason why companies are more likely to find funding is due to the fact that capitals attract more international and diverse people who concentrate their talents in the capital. It is more of a case of the talent being concentrated and capital (money) being more readily available than the legislative environment, but for some business models it may be important to be close to legislative bodies.*
	Finding 3: Startups led by CEOs with a bachelor's degree or a doctorate are more likely to secure funding within three years. Question: How important do you think a CEO's degree is in influencing a startup's fundraising success?	*According to the interviewee, the finding is surprising, especially since in practice it is observed that many successful fundraising companies have CEOs with master's degrees. This is a surprising finding and not observed on the venture capital side.*	*According to the interview subject, the finding makes sense that higher levels of education have a positive effect, but the specific degrees are surprising. At the end of the day, what investors are expecting is the career path. The degree only helps to get the first job. After the*

			second job, no one cares. VCs want to invest in teams rather than degrees. However, generally speaking, a bachelor's degree is a prerequisite for many aspects of building a network and thus an interesting firm for investors. PhDs are usually valuable for niche deep tech ventures where the previous research is highly valuable. This makes the firms more investable.
	Finding 4: Crypto-focused startups are less likely to raise funds within three years, Startups offering software as a service (SaaS) are more likely to receive subsequent funding within three years. Question: Do you agree with the finding and what is causing the impact on ability to raise funds and why is that in your experience?	*Investor completely agrees. Crypto startups post-first investment often reach a stage where it is more lucrative to conduct an initial crypto offering rather and they thus do not seek formal external funding from investors. When it comes to SaaS focused firms they are generally favored by investors and attractive due to the stable revenue generation model*	*According to the interview subject, this makes sense. Investors like to invest in SaaS companies because of the revenue generation model, making it more attractive to investors compared to other revenue models where the income streams might be more volatile. When it comes to crypto, this also makes sense. ICOs and high-risk ventures with late revenue generation make them less attractive to investors.*
	Finding 5: Startups initially funded by accelerators or incubators are less likely to raise funds again within three years. Question: What challenges might fintech startups face if their initial funding comes from accelerators or incubators? Are there specific factors related to these funding sources that might impact subsequent fundraising efforts?	*The interviewee is unsure. Some of the best teams did not want to seek investment from external sources in the very early stages of business development. Rather, many of them used bootstrapped financing methods in order to get through the initial phase of the development of the fintech startup.*	*According to the interview subject, accelerators make it more difficult to invest afterwards. Many accelerators have terms that take a lot of equity from the firms in the initial development phase, making them less attractive to investors. They also are involved heavily in the managerial and strategic decisions the company makes, making it additionally less attractive to prospective investors.*
Subsequent funding within two years findings	Finding 1: A higher number of initial investors is positively related to the likelihood of subsequent funding within two years. Is this reflected in your experience and what could be causing it?	*According to the interviewee, having more investors in a deal is not necessarily predictive of success. In practice, many investors are very passive and do not add much value beyond providing financial means to the firm's success.*	*According to the interview subject, more investors mean a bigger network. By having multiple investors on board, it can be easier to find sources of subsequent investment later. However, from a managerial standpoint, it is actually quite complicated having many investors holding equity in the company.*
	Finding 2: Startups in the initial development phase and not yet generating revenue are more likely to receive subsequent funding within two years. Is this reflected in your experience and what could be causing it?	*According to the interviewee, this makes a lot of sense. Investors might be drawn to companies because they have a clear plan and a good vision, but at that specific stage, they are not generating any revenue and are focusing on finding*	*The interviewee finds this unexpected. Generally speaking, investors are typically seeking out prospective investments where there are existing customers and revenue generation is already*

		product-market fit or are generally in the development phase. This creates an attractive environment for investors, especially if they are actively involved in guiding the startup.	*happening at the time of investment.*
	Finding 3: Startups led by CEOs with a bachelor's degree are more likely to secure funding within two years. Is this reflected in your experience and what could be causing it?	*The interviewee agrees that this finding makes partial sense and is reflected in the real world. Usually, many people with post-graduate degrees are the most successful at fundraising and generally achieve long-term success with their startups. However, the interviewee notes that having a bachelor's degree does not necessarily make a significant difference in the real world.*	*The interviewee claims that this is more of a pre-requisite than anything else in his view*
	Finding 4: Startups providing mobile services are more likely to raise funds within two years. Crypto-focused startups are less likely to raise funds within two years. Is this reflected in your experience and what could be causing it?	*According to the interviewee, this makes sense. Investment into mobile-focused companies often follows a predictable pattern, allowing startups to align with the 18–24-month investment cycle. The interviewee also notes that the investigated timeframe of 2010-2020 matches the boom of mobile technology, which could contribute to the positive predictive power. However, when it comes to crypto firms, they often turn to ICOs, which is not necessarily reflective of their ability to raise funds through traditional means.*	*The interviewee agrees, stating that this makes sense. Mobile-focused fintech startups are inherently more likely to focus on B2C, which enables them to generate revenue earlier than firms outside of the mobile sector. Regarding crypto, the interviewee notes that the reliance on ICOs and the perceived risk of investing in crypto-focused startups is understandable. They also mention that there was a significant drop in interest after the prices of cryptocurrencies crashed.*
	Finding 5: Startups initially funded by grants are more likely to receive subsequent funding within two years. Is this reflected in your experience and what could be causing it?	*The interviewee states that this observation aligns with what is seen in the real world and makes complete sense. It can be explained by two main factors. First, grant funding amounts are lower and are achieved more slowly, which might necessitate another subsequent round of funding sooner. Second, founders who are very focused and bullish on gathering any type of funding might be inclined to look for grants among other types of funding.*	*According to the interviewee, this makes sense. Grants are often difficult to access and are not adjusted to the cash burn rate of companies. This makes firms financed by grants more prone to seeking subsequent funding more quickly than those not financed by grants.*
Subsequent funding within one year	Finding 1: Smaller initial investments are associated with a higher likelihood of subsequent funding within one year. Is this reflected in your experience and what could be causing it?	*According to the interviewee, this makes sense. The initial smaller funding may result in a shorter funding cycle or create the need for bridge financing.*	*The interviewee acknowledges this point, noting that it could be related to the cash burn rate, but generally there is no clear pattern.*
	Finding 2: A higher number of initial investors is positively correlated with the likelihood of subsequent funding within one year.	*The interviewee notes that this is not observed in practice and is not considered a qualitatively positive or negative predictor of funding or success, as stated before.*	*The interviewee agrees, noting that a bigger network means a higher number of people opening doors and aiding with access to*

	Is this reflected in your experience and what could be causing it?		*subsequent funding when it becomes necessary.*
	Finding 3: Startups that disclose their employee numbers publicly are more likely to raise funds within one year. Is this reflected in your experience and what could be causing it?	*The interviewee states that the finding is not reflective of the real world. Staffing, in general, is a contentious topic because post-funding CEOs may hire too many people, but the disclosure itself is not reflective of anything in practice.*	*The interviewee expresses uncertainty about whether this makes any difference in practice or why this was observed. They cannot explain it, and note that in their experience, this type of effect is not reflected in practice.*
	Finding 4: Fintech startups in the technology, media, and telecom (TMT) sector are more likely to raise funds within one year. Is this reflected in your experience and what could be causing it?	*This finding is not reflected in practice and is unclear what is causing it*	*The interviewee finds the finding interesting but notes that it is difficult to say why this is the case. They are unsure what may be causing this.*
	Finding 5: Startups receiving early-stage venture capital investment as their first formal investment are less likely to raise funds within one year, whilst those receiving grants are more likely to raise funds within one year of the initial deal. Is this reflected in your experience and what could be causing it?	*According to the interviewee, early-stage venture capital as the first funding can be a positive predictor. Some investors achieve this by initially using bootstrapped financing methods and figuring out ad-hoc ways before receiving the first formal external financing. The interviewee finds this finding valid based on their experience.*	*According to the interviewee, this makes sense and is logical. Firms that bootstrapped their way until their initial fundraise at an early series VC investment stage were able to keep all their equity, making them more attractive to investors. It also indicates that the company has reached a stage where they need financing; otherwise, they would not have sought external sources.*
Variables that were not found to statistically significant predictors	(Showing investigated variables). All other variables that were not discussed were not found to be statistically significant. Do you find this odd? Is there an effect you would expect to be significant?	*The interviewee finds that the macro factors are notable, but this is actually completely in line with their expectations. They explain that the number of investors is appropriate for the available capital in the VC market, and they essentially 'correct' for the macro effects, finding an equilibrium.*	-
Closing	Thank you for sharing your insights. It is valuable when it comes to validating the quantitative findings from the conducted research. Is this reflected in your experience and what could be causing it?	-	-

Source: Interviews conducted by author. Full recorded videos and full transcripts available upon request and consent of interviewees.

Affidavit

ESCP Business School

I, the undersigned, do hereby state that I have not plagiarised the paper enclosed and that I am the only author of all sentences within this text. Any sentence included which was written by another author was placed within quotation marks, with explicit indication of its source. I am aware that by contravening the stated ESCP Business School rules on plagiarism, I break the recognised academic principles and I expose myself to sanctions upon which the disciplinary committee will decide.

I also confirm this work has not previously been submitted during studies prior to ESCP Business School. If this work has been written during studies conducted in parallel to my time at ESCP Business School, I must state it.

I accept full responsibility for the content of this paper.

.... (Signature)

András Dunay .... (Print name)

29.05.2024 .... (Day/month/year)