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THE ROLE OF FOUNDERS IN VENTURE CAPITAL FUNDING – AN EMPIRICAL ANALYSIS OF GERMAN START-UPS

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Abstract

This paper examines the impact of start-up founders' backgrounds on the venture capital funding raised. In the analysis, different factors such as gender, education, and professional experience are used to test the influence on the collected venture capital. Results show that gender has no significant impact on funding. Education has both a positive and negative significant effect depending on different levels of education. The university attended and industry experience have a significant positive influence on the funding amount. Founding experience shows a negative significant effect on funding. However, no significant connection to tech experience could be established.

Keywords

Venture capital funding, start-up financing, founder background, gender gap, human capital

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1. Introduction

In 2021 global venture capital investors made record-breaking investments in start-ups, nearly doubling in size to a total of 675 billion US dollars (Shead 2022). This almost corresponds to three times the economic output of Portugal in 2021 (IMF 2022). The USA continues to account for almost 50% of all global investments, however Europe is catching up and can report the highest growth rate compared to the previous year (Shead 2022). But how are these huge amounts of capital allocated? The venture capital market's key characteristic is the bilateral matching of investors and start-ups. On the one hand, there are investors, who are provided with countless pitch decks and business plans (Bengtsson and Hsu 2010). On the other hand, founders[1] have to find venture capitalists who fit them best. Fit is not only influenced by monetary support, but also by strategic considerations such as finding a suitable partner (Bengtsson and Hsu 2010). However, this paper is not about the selection of the venture capitalist from the perspective of the start-up founder. A venture capitalist must thoroughly investigate a company before investing. Such an investment carries a considerable risk, as can be shown by looking at the failure rates of start-ups. According to the global start-up ecosystem report 2022 the failure rate of all start-ups founded worldwide remains at 90% (Gauthier et al. 2022). Among the start-ups that do not fail, only a small fraction generates double million-digit exit values. Gauthier et al. (2022) found that only 1.5% of all start-ups generate an exit of 50 million US dollars or more. Conversely, this means that investors make a real profit only with a fraction of their investments and thus must also compensate the failed investments with the few profitable ones (Zider 1998).

In the light of the aforementioned, the question arises what criteria venture capitalists apply to select their start-up investments. There is a great deal of disagreement among academics and

[1] In the following, the terms entrepreneur, start-up founder and founder are used as synonyms.

professionals regarding the most crucial screening and selection criteria. This is why in the literature a controverse discussion about which factors are most relevant for investment selection takes place (Gompers et al. 2020). For example Kaplan and Stroemberg (2004) support earlier findings showing that venture capitalists especially consider aspects such as market attractiveness, strategy, technology, product or service, competition, deal conditions, and the management team. Although there is a quite broad discourse on the decision criteria, their weighting is underexplored. In consequence, there is little information about which of the points has a significant impact on the investment decision. Other research focuses on how start-up founding teams are built and increase the attractiveness of the start-up to the venture capitalist (Hellmann and Puri 2000). The empirical study by Gompers et al. (2020) shows new perspectives on the extent to which the business-related facts mentioned are of relevance. In a large-scale survey of almost 900 institutional venture capitalists, the importance of various investment criteria was assessed. Almost half of the respondents stated that the founding team was the most important criterion in the investment decision, and 95% of the venture capital firms surveyed considered it to be an important criterion. This is followed by the business model with 83%, the product with 74%, the market with 68% and the industry with 31% importance. Overall, only 37% considered these hard facts as very important. Taking into account that the quality of the founding team is of such great relevance in practice, it is a logical consequence to ask which criteria, in particular the qualities and references of the founders, are important for the VCs[2]. However, the quality of the founder depends on many factors. The literature often refers to the human capital theory, which was initially invented by Becker (1962). Following this theory, it is mainly knowledge and experience and the resulting skills and relationships that are referred to as human capital (Frese and Rauch 2001). Considering that existing literature

[2] VCs, VC, venture capital firms, venture capitalists, and investors, are used interchangeably.

has only partly explored the influence of the founders' background on the funding amount, this paper will try to fill this research gap with a holistic approach. Hence, this paper tries to answer the following research question: "Does the gender, education and professional experience of a start-up founder influence the venture capital funding raised?"

The results of the analysis show that the level of education has a significant influence on the collected capital. This effect is both negative and positive depending on different levels of education. Furthermore, it can be observed that universities with better reputation have positive influence on the funding. The same effect can be identified for the industry experience, which also has a positive significant influence. Founding experience shows a negative significant effect on funding. In contrast, neither a significant relationship could be established between gender and funding nor between tech experience and funding. For obtaining these results, this paper is structured as follows. First, the theoretical background is described, and existing literature is presented. The theoretical background is the foundation for the development of the hypotheses. Afterwards, the research methodology is demonstrated. Therefore, details regarding the data and sample construction, information on the dependent, independent, and control variables and the estimation method are illustrated. In the fourth chapter the examination of the data is performed, descriptive statistics and the regression analysis are displayed and contextualized. In the last chapter the interpretation, the limitations of the study and suggestions for future research are discussed.

2. Literature review

2.1. Start-up founders' gender

Previous research from various disciplines in economics, examined the relationship between the gender of the start-up founder and external financing. The literature to date largely agrees that female start-up founders have to overcome considerably greater hurdles in order to obtain such financing, especially in the case of venture capital (Greene et al. 2001). A study by Demartini (2018) finds that, on average, female start-up founders receive less equity funding than men. The analysis of the financial statements of 226 Italian start-ups, revealed that, on average, women-owned businesses had lower levels of equity and even higher borrowing costs than male-owned start-ups (Demartini 2018). This is in line with the results of the meta-analysis by Geiger (2020) which also found that there is a discrepancy in the amount of external capital to the disadvantage of female entrepreneurs. However, there is no clear picture when it comes to other external types of financing, such as crowdfunding, where female capital seekers tend to have an advantage over male entrepreneurs (Johnson, Stevenson, and Letwin 2018).

2.2. Start-up founders' education and top tier universities

In earlier stages of start-up financing, there is an increased risk for investors, as there is no basis for a quantitative investment decision due to the lack of historical business activity (Ratzinger et al. 2018). There are different theories how potential investors deal with such missing information. The so-called signal theory describes signals which are supposed to reduce the information asymmetry between the entrepreneur and the investors (Islam, Fremeth, and Marcus 2018). As already stated, knowledge is a component of human capital and can be acknowledged as an intellectual asset which may help to create a competitive advantage in the future (Dimov and Shepherd 2005). Knowledge consists of implicit and codified components. Implicit knowledge is difficult to detect, but codified knowledge can be imparted through the education of the entrepreneurs. Therefore, the founder's formal education, such as a university

degree, can be considered as codified knowledge and hence as human capital. For that reason investors interpret the education as an important signal, especially for early stage investments (Franco, Cappa, and Pinelli 2021). Existing empirical analyses have shown that there is a positive correlation between academic education and venture capital funding. In an analysis by Ratzinger et al. (2018), the correlation between the education of digital start-up founders and the achievement of investment milestones, i.e., funding or exit, was tested. Results show that business and general education are statistically important predictors of the attainment of funding milestones by digital start-ups. This is consistent with the results of Franco, Cappa, and Pinelli (2021). Using a sample of 1,725 founders of American start-ups, a correlation is found between education and the capital raised. This means that the more educated the founders are, the better is the access to external financing. In this context, the literature often mentions not only the degree, but also the type of university. This generally refers to whether the founder was educated at a university which appears in common rankings[3]. The literature is mainly concerned whether a university, where statistically more start-up founders are educated, has an advantage due to the strong alumni network effects. The study of Nann et al. (2010) shows that the stronger the connection to the alumni network of the universities, the more positive the impact on the performance of the start-up. These networks are particularly encouraged at these top tier universities. Contrary to the previous findings the analysis of Roche, Conti, and Rothaermel (2020) outline that the amount of money raised is not statistically significant affected by the founding team members' university backgrounds.

[3] Among the most popular university rankings are: CHE-Ranking, FT-Ranking, QS World University Ranking, Shanghai Ranking and Times Higher Education World Ranking (see Fischer 2021). All rankings have different evaluation methods, some consider research activity, some consider student opinion. This makes it difficult to compare the results. Generally, universities that are ranked at the top of these rankings are among the top tier universities in their country.

2.3. Start-up founders' professional experience

2.3.1. Founding experience

One factor that plays a major role when it comes to prior experience, is the previous founding experience of the entrepreneur. There are several reasons why existing founding experience can help start-ups to access venture capital funding. Firstly, it can be emanated that serial founders[4] have more extensive skills to build up the second company faster and more efficiently based on the knowledge gained during the initial founding process (Zhang 2011). Furthermore, the founder was already able to make contacts during the previous start-up time, which contributes significantly to the human capital (Hsu 2007). In view of these aspects, there are empirical analyses which predominantly show a positive effect of founding experience on the venture capital funding process. The findings of Zhang (2011) with a total sample of 10,520 founders not only show that, on average, start-ups with experienced founders have faster access to venture capital, but also that these funding amounts are higher in the first round of financing than those of start-ups with inexperienced founders. These findings are also in line with a more generic study on the performance of start-ups with experienced founders. It found that start-ups with at least one serial founder in the founding team perform better than those without (Colombo and Grilli 2005).

2.3.2. Industry and tech experience

Another potential determinant of the relationship between the start-up founder's background and the funding amount is the industry experience. Industry experience refers to the experience which the start-up founder has gained in a previous position within the same industry in which the start-up operates (West III and Noel 2009). The literature is largely in agreement that founders' industry-specific knowledge generally enhances the performance of the start-up

[4] This terminology is used to describe a founder who has already founded another start-up before the current one (Bengtsson 2013).

(Colombo and Grilli 2005). Research by Cooper (1994) and Siegel et al. (1993) concurring demonstrate that prior industry experience contributes significantly to start-ups survival, growth and success. The results of a recent large-scale panel study show that start-ups reach profitability faster if their founders have experience in the industry in which the start-up operates (Oe and Mitsuhashi 2013). The study by Grilli et al. (2020) also agrees with the results mentioned above. Using a dataset consisting of Italian tech start-ups, a positive effect is measured between the founders' industry knowledge and the start-ups performance. Colombo and Grilli (2005) even find that the technical experience has an even stronger effect than the commercial industry experience on the growth of the start-up. This result is equally interesting for this paper, as the underlying data set has a high proportion of companies that are directly or indirectly associated with software.

2.4. Development of hypotheses

After outlining the theoretical basis of this paper, in this chapter the hypotheses are derived. Thereby theoretical inferences and empirical results of previous literature are taken into account. First, based on the previous presentation it can be concluded that the gender of the founder plays a significant role in both access and the amount of funding. This paper follows the results of previous research and assumes that male start-up founders on average receive a higher funding amount than female start-up founders. This leads to the following hypothesis:

H1: Male start-up founders raise a higher amount of venture capital funding compared to female start-up founders.

Second, the literature review has shown that the level of education of a founder is a decisive criterion for venture capitalists and therefore might have a positive effect on the funding process. Following the previous literature in connection with the objective of this study, the following hypothesis emerges:

H2a: Start-up founders with higher education raise a higher amount of venture capital funding.

In chapter 2.2 it has been shown that not only the degree but also the attended university of a founder could affect the success of the start-up and its access to venture capital. Existing literature does not provide a clear picture whether the academic institution has an influence on the funding amount. In this paper, the assumption will be made that the reputation of the educational institution could play a role in the funding process. Therefore, this leads to the following hypothesis:

H2b: Start-up founders with a degree from top tier universities raise a higher amount of venture capital funding than founders from non-top tier universities.

Moreover, literature on the relationship between founder's previous professional experience and the start-up success was explained. Previous start-up experience seems to be of particular importance. The literature largely agrees that start-ups founded by founders with experience have a higher chance of success and additionally an advantage in the venture capital process compared to founders with no founding experience. Thus, it can be hypothesized:

H3a: Start-up founders with prior founding experience raise a higher amount of venture capital funding than founders without prior founding experience.

The studies cited on industry knowledge clearly show that the performance of the start-up increases with industry experience. This in turn means that investors potentially provide more capital due to the better performance, which can be formulated in a hypothesis as follows:

H3b: Start-up founders with prior industry experience raise a higher amount of venture capital funding than founders without prior industry experience.

The underlying data set was not restricted to software companies, yet according to the data source a large proportion of the companies is related to software. As mentioned in chapter 2.3.2, there is also a connection between the technical experience and the performance of the start-up,

which is why the following hypothesis emerges:

H3c: Start-up founders with prior tech experience raise a higher amount of venture capital funding than founders without prior tech experience.

3. Research design and methodology

3.1. Data collection

For the purpose of this research, there is no database that can provide necessary information in aggregated form. Therefore, a self-generated data set, which is ideally suited for the regressions, was created with the help of various sources. The basis of the data is provided by Crunchbase[5], which is a common database including information about start-ups, start-up industry, founding date, funding stage and rounds, founding members, etc. Crunchbase has been used in previous venture capital research, for example by Block and Sandner (2011), Wu (2016), Ratzinger et al. (2018), Roche, Conti, and Rothaermel (2020). In particular, Wu (2016) explicitly points out the validity of current data of Crunchbase in his study. This base from Crunchbase provides the data foundation but does not include information on the background of the founders necessary for this sample. Therefore, in the second step, this list of start-up founders is used to hand-collect the necessary information, i.e., gender, education, professional experience, using LinkedIn[6]. This method was also partly used by the mentioned paper to fill information gaps.

3.2. Sample construction

The existing literature mainly deals with US start-ups, possibly because it has by far the largest number of start-ups and therefore the largest venture capital market in the world. In the sample, however, I explicitly do not test with US start-ups, but use data from the second largest European venture capital market, Germany. Due to the size of this venture capital market, one might expect the German start-up market to be able to provide a representative and complete

[5] www.crunchbase.com
[6] www.linkedin.com

set of data in a European comparison. An attempt is made to negate potential influences of the COVID-19 pandemic using the period filter. Therefore, the founded date filter of the start-ups is set from 01/2015 to 12/2019 to exclude start-ups founded during the pandemic. The level of venture capital investments was not only brought up to the pre-crisis level of 2019, but was nearly doubled in 2021 (Shead 2022). Hence, only start-ups that received their last funding in the period from 01/2021 to 09/2022 are included.[7] In order to be able to test the previous hypotheses in a comprehensible way, only start-ups with seed as the last funding type are included in the data set. Zhang (2011) provides a rationale for this: As start-ups get bigger, their success might depend less and less on their founders. Therefore, the dataset focuses on early-stage companies to take into account the importance of venture capitalists' decision-making criteria for younger start-ups. Furthermore, only three of all start-ups were not operating anymore and for two corresponding information was missing. This means that only one start-up in the sample is considered closed, which in turn could lead to a survivorship bias in the overall analysis.[8] Considering all the points listed, this leads to an initial number of 334 start-ups in total. Due to missing information on the names of the founders and/or the amount of funding, a total of 177 start-ups are removed from the sample, resulting in a total of 157 remaining start-ups with all necessary information. These 157 start-ups have a total of 370 founders. Of these 370 founders, the information of 55 could not be found. Summarizing all process steps, the final dataset contains a total of 315 founders corresponding to 148 start-ups with funding amount between 01/21 to 09/22 and their respective gender, education, founding experience, industry experience, and tech experience. Figure 1 in the appendix shows the process of sample construction.

[7] Nevertheless, the description of the control variables in chapter 3.5. shows that the time factor is controlled.
[8] This issue will be further highlighted in chapter 5 within the limitations.

3.3. Dependent variable

The dependent variable funding corresponds to the absolute funding amount in euro raised by the start-up in its last funding round, i.e., the seed round. In the course of this analysis, this variable is also log-transformed. This is in line with several previous papers such as: Demartini (2018) and Franco, Cappa, and Pinelli (2021) who also use the funding amount as a dependent variable in their analysis. Since the download provided by Crunchbase shows the funding amount partly in dollars, a currency conversion to a uniform basis in euro is created using the average exchange rates of the respective years 2021 and 2022.

3.4. Independent variables

To test hypothesis 1, the variable gender either takes the value one if the respective founder is male or zero if the founder is female. In the context of data collection, it was presumed that the founders identify themselves as male or female on the basis of their first name and profile picture. Analogous to gender, the variable education represents the following four dichotomous variables: 'No degree', 'Bachelor', 'Master', 'PhD'. Only the highest educational degree of the founder was documented in the research. Furthermore, the following assumptions were made: if no educational degree was visible on the LinkedIn profile, but the LinkedIn profile was nevertheless considered complete, then the founder’s education was categorized as ‘no degree'. Likewise, an apprenticeship was documented as a 'no degree'. Furthermore, the former German equivalent to the current master's degree 'Diplom' and the degree 'MBA' was documented as a master degree. As part of the research on the founders' degrees, the university of the highest degree was also recorded to determine the variable top tier university. This variable equals one if the founder attended a top tier university and zero if not. For this purpose, the ranking Times Higher Education from the year 2021 was used to check whether the university in question is ranked among the top 15 universities in the respective country. Table 1 in the appendix shows an overview which universities fall into this category. Turning now to the professional

experience of the founders. First, the variable founding experience: if a founder has already founded a start-up, the variable takes a value of one, otherwise zero. It was important to ensure that valid founding experience was available by also looking at the previously founded companies, if possible. Another independent variable is industry experience, which is also dichotomous in nature. The presence of industry experience is given if the founder has experience in the same industry in which the start-up operates. For example, if a start-up sells software that is active in the financial services sector, then the founder is only credited with industry experience if experience was gained in the financial services sector. Therefore, the variable tech experience, also a dichotomous variable, is added which covers the experience as for example software developer in another area than financial services. Experience in consulting and venture capital was also collected but not used further for the analysis. The hand-collected approach, the selection and collection of variables is similar to previous papers such as (Bengtsson and Hsu 2010). Table 2 in the appendix provides an overview of the data collection of the founders' biographies.

3.5. Control variables

The dependent variable funding amount might be influenced by many other factors than the independent variables just mentioned, which is why this study includes several control variables. It is further noted that in the context of different models, different inclusions or exclusions of control variables take place, more on this in chapter 3.6. In the following, particular reference is made to Zhang (2011) and Roche, Conti, & Rothaermel (2020) when discussing the control variables. The industry control variable is necessary as different industries have different capital requirements. Accordingly, companies from more capital-intensive industries will raise higher funding amounts. For this purpose, this study includes a categorical variable for 20 industries, which equals to one if the respective industry applies otherwise zero. Due to the almost 70 percent share of companies that are directly or indirectly

classified as software related companies by crunchbase, the control variable software is introduced which indicates whether the founder's start-up works with software, equal to one, or not, equal to zero. Furthermore, the age of the start-up is controlled. The variable start-up age indicates the time between foundation and the funding date on yearly basis. Since macroeconomic changes have occurred in particular in 2022 (see Khudaykulova et al. 2022), an attempt is made to control time by introducing the variable funding date. Since the underlying data is a cross sectional dataset, a time fixed effects method is established using a set of dummy variables (Wooldridge 2010). Hence, the dummy variables take the value one if the funding was performed in the respective month otherwise zero. Furthermore, this study controls the size of the company with the help of the employee headcount which was also surveyed using LinkedIn. One would expect the size of the company to increase as the number of employees increases, simultaneously the need for capital. Although a filter was already set for the seed funding stage during data collection, a control variable is introduced to show how many funding rounds have taken place before the most recent funding round. There are also cases where start-ups carry out several pre-seed rounds before the seed round. It could also be assumed that there is a positive correlation with the funding amount, since the funding amount usually increases with an increasing number of funding rounds. Related to this is the number of investors to be controlled in this study. Finally, the control variable state, which represents the location within Germany's federal states of the start-up's headquarters, is intended to control local trends. This variable uses the same dummy variables technique as industry and funding date. Table 3 in the appendix provides an overview of all variables used in the analysis.

3.6. Estimation method

The following section deals with models that are used to test the developed hypothesis. A total of four different models with different specifications are tested. In all models, the following assumptions apply: α shows the intercept, β_n display the coefficients, and ε constitutes the error

term. The first model includes all the variables described except for the control variables industry, funding date and state. Given the limited size of the sample the main goal is to avoid a too complex model, which especially occurs when there are too many parameters in relation to the observations. Furthermore, funding date is exculpated in model 1 since an attempt was already made to control this factor during the data collection by filtering relatively compressed time. The same applies to variable state, since the fundings were only carried out within Germany.

$$\begin{aligned} Funding = \ & \alpha + \beta_1 Gender + \beta_2 Education + \beta_3 Top\ tier\ University \\ & + \beta_4 Founding\ Experience + \beta_5 Industry\ Experience \\ & + \beta_6 Tech\ Experience + \beta_7 Software + \beta_8 Startup\ Age \\ & + \beta_9 Employee\ Headcount + \beta_{10} Funding\ Rounds \\ & + \beta_{11} Number\ of\ Investors + \varepsilon \end{aligned}$$

Model 1: Equation

The second model attempts to further minimize the influence on funding amount with the help of the fixed effects and tries to bring even more explanatory power into the regression.

$$\begin{aligned} Funding = \ & \alpha + \beta_1 Gender + \beta_2 Education + \beta_3 Top\ tier\ University \\ & + \beta_4 Founding\ Experience + \beta_5 Industry\ Experience \\ & + \beta_6 Tech\ Experience + \beta_7 Software + \beta_8 Startup\ Age \\ & + \beta_9 Employee\ Headcount + \beta_{10} Funding\ Rounds \\ & + \beta_{11} Number\ of\ Investors + \beta_{12} State + \beta_{13} Industry \\ & + \beta_{14} Funding\ Date + \varepsilon \end{aligned}$$

Model 2: Equation

There are previous studies where the numerical variables were not log-transformed, and there are papers which log-transform all numerical variables. The data examination in the next chapter will show that some of the variables have a skewed distribution. To note that and also follow previous literature (see Conti et al. 2019; Roche, Conti, and Rothaermel 2020), model 3 and model 4 are used to perform a regression with selected log-transformed numerical variables.

$$\log(Funding) = \alpha + \beta_1 Gender + \beta_2 Education + \beta_3 Top\ tier\ University + \beta_4 Founding\ Experience + \beta_5 Industry\ Experience + \beta_6 Tech\ Experience + \beta_7 Software + \beta_8 Startup\ Age + \beta_9 log(Employee\ Headcount) + \beta_{10} Funding\ Rounds + \beta_{11} Number\ of\ Investor + \varepsilon$$

Model 3: Equation

Model 3 uses the same control variable specification as model 1 and model 4 uses the same variables as model 2. The breakdown of the models can be retraced in table 6 in the appendix.

$$\log(Funding) = \alpha + \beta_1 Gender + \beta_2 Education + \beta_3 Top\ tier\ University + \beta_4 Founding\ Experience + \beta_5 Industry\ Experience + \beta_6 Tech\ Experience + \beta_7 Software + \beta_8 Startup\ Age + \beta_9 log(Employee\ Headcount) + \beta_{10} Funding\ Rounds + \beta_{11} Number\ of\ Investors + \beta_{12} State + \beta_{13} Industry + \beta_{14} Funding\ Date + \varepsilon$$

Model 4: Equation

All four models contain the variables to address all hypotheses. This strategy of different specifications tries to generate a holistic empirical picture.

4. Analysis and results

4.1. Data examination

The statistical analysis was performed using the software Stata/MP 17.0 for Mac. Furthermore, the corresponding tables were created using Microsoft Excel. Except for start-up age, outliers were detected for all numerical variables. These were determined using a boxplot and the default inter quartile range of 1.5 (see figure 2 in appendix). In the literature, there is a relatively clear definition of outliers, but no uniform approach of dealing with them because it always depends on the individual circumstances. There are real and fake outliers, the latter are errors in the data. Such errors can arise especially during the data collection process (Yang and Berdine 2016). After a thorough examination of the underlying data set, it can be assumed that there are no apparent errors. Due to the extreme heterogeneity of the start-ups in the dataset

these outliers represent valid observations and therefore natural variation in the sample. This is the reason why these datapoints are not dropped from the sample. Furthermore, the dependent and non-binary control variables are checked whether they follow a normal distribution. This check takes place with the help of density plots. The result shows that none of the variables are normally distributed (see figure 3 in appendix). Hence, a log transformation of the variables was performed. The graphical analysis of the density plots after the transformation shows that the variables funding and employee headcount are now normally distributed (see figure 4 in appendix). For the other variables, the non-normality could not be improved. Hence, for model 3 and 4 the natural logarithm of the variables funding, and employee headcount was used.

4.2. Descriptive statistics

Table 4 in the appendix shows a summary of the descriptive statistics of all numerical variables. The maximum amount of funding in the sample corresponds to 30m euro and the minimum to 25k euro. Hence, it makes sense to normalize the dependent variable in models 3 and 4, as explained in the previous chapter. Furthermore, almost 85% of the founders in the sample are male. The largest share of all founders has a master's degree, at just under 54%. This is followed by a bachelor's degree with around a quarter and just under 17% with a PhD. Founders without a higher education degree are underrepresented, accounting for around 4% of all founders in this dataset. About every third degree was obtained from this papers' definition of top tier university. Approximately 36% of the founders have already founded a start-up before. One out of three founder has industry experience and just over 27% also have tech experience. Looking at the correlation of the variables, the dependent variable is negatively and significantly related to variables gender, founding experience, software. Hence being a man and having founding experience has negative impact on funding. This generally contradicts the assumed relationships. Furthermore, the variable funding is positively related to industry experience, employee headcount and number of investors. This in turn is consistent with the assumptions

made. For example, because companies with a larger number of employees require more capital. With regard to the correlations within the independent variables, it must be said that the correlation analysis of the variables is performed with the reference group no degree. This means that all correlations within the variable education are interpreted in relation to the omitted variable no degree. As a matter of necessity these correlations have a negative sign and are significant since they have an academic background unlike the no degree reference group. Otherwise, significant, and increased correlations are still noticeable for the following variables: positive correlation between funding rounds and start-up age as well as positive correlation between number of investors and employee headcount. This seems also coherent, since with increasing start-up age the funding rounds increase. One explanation for the increasing number of investors with increasing employee headcount could be due to an increased employee headcount an increased capital requirement is necessary and therefore more investors are needed. Please refer to table 5 in the appendix for an overview of the correlations.

4.3. Regression analysis

In the following, reference is made to table 6, 7 and 8 in the appendix, which show the overview of all models performed. These models are estimated using Ordinary Least Squares. To properly present the results for hypothesis 2a, the educational level was iteratively compared to the next higher level (bachelor compared to no degree, master compared to bachelor and PhD compared to master). Hence, tables 6, 7 and 8 show the regression outputs for the different reference categories. First, the base models 1 and 2 are discussed and then the results of model 3 and 4 with log specification are presented.

Model 1 has an explanatory value of 24.5% (r-squared) which means that about a quarter of the variance for the variable funding can be explained by the independent variables and the applied control variables. With the introduction of the fixed effects variables state, industry, and funding date this value can be increased significantly to 56.8% in model 2. Model 1 shows a negative

but insignificant influence of gender on funding (model 1: β_1 = -677,786; $p > 0.1$). This is consistent with the coefficient from model 2, where it also has a negative but insignificant effect (model 2: β_1 = -300,846; $p > 0.1$). With the introduction of the fixed effects controls, it can be observed that this negative effect is approximately halved. Hence, as these effects are insignificant, model 1 and model 2 are not sufficient to find support for hypothesis 1. Furthermore, a bachelor's degree compared to no degree shows a negative impact on funding (model 1 β_2 – bachelor: -100,721; model 2 β_2 – bachelor: -647,414; $p > 0.1$). A master's degree compared to a bachelor's degree also shows a negative impact on funding (model 1 β_2 – master: -410,799; model 2 β_2 – master: -557,966; $p > 0.1$). Lastly having a PhD title compared to a master's degree unveils a positive impact on funding (model 1 β_2 – PhD: 784,206; model 2 β_2 – PhD: 490,291; $p > 0.1$). However, these values are insignificant along all education levels. Accordingly, models 1 and 2 are not sufficient to support hypothesis 2a. The variable top tier university in model 1 indicates a positive but insignificant coefficient (model 1: β_3 = 559,454; $p > 0.1$). In model 2, positive influence can be observed too, but in this case the coefficient is significant (model 2: β_3 = 936,548; $p < 0.05$). The results from Model 2 provide support for hypothesis 2b. Since this variable is a dummy variable, the coefficient does not indicate the marginal effect but an intercept shifting effect. Hence in the case of the variable equals to one, i.e., if the founder attended a top tier university, the intercept shifts by the value of the coefficient. As a result, keeping all other factors constant, the intercept shifts by +937k euro in model 2. As hypothesis 3a states that experienced founders would raise more capital, the coefficient β_4 has to be considered. In model 1 the negative and significant coefficient (model 1: β_4 = -926,006; $p < 0.05$) implies that there is a negative relationship between the funding amount and the founding experience. Model 2 also shows a negative but insignificant influence (model 2: β_4 = -343,679; $p > 0.1$). The results from model 1 reject hypothesis 3a because the presence of founding experience reduces the funding amount by decreasing the intercept by

almost one million euro. A notably uniform picture emerges for the variable industry experience and the associated hypothesis 3b. In both model 1 and model 2, the coefficients are significant and positive (model 1: β_5 = 1,009,288; model 2: β_5 = 813,072; $p < 0.05$). Thus, both models provide support for hypothesis 3b. Ceteris paribus, the intercept shifts by just over one million euro in model 1 and about 800k euro in model 2. Apart from that, model 1 and model 2 find no support for hypothesis 3c since in model 1 and in model 2 the positive coefficients are not significant (model 1: β_6 = 376,215; model 2: β_6 = 201,066; $p > 0.1$). Turning to the results of the regression with the log transformed variables, models 3 and 4. First, it can be seen that the explanatory power of the two models has increased with the help of the normalization of the funding and employee headcount variable compared to model 1 and model 2. Model 3 has an r-squared value of 43.3% and model 4 a value of 63.2%. The results for variable gender are consistent with the previous two models, i.e., there is a negative but insignificant influence (model 3: β_1 = -0.198; model 4: β_1 = -0.133; $p > 0.1$). Therefore, models 3 and 4 also find no support for hypothesis 1. However, differences in significance can be observed regarding the education variable. Since a bachelor's degree compared to no degree shows a negative and significant impact on funding (model 3 β_2 – bachelor: -0.508; model 4 β_2 – bachelor: -0.511; $p < 0.1$). Furthermore, holding a master's degree compared to a bachelor's degree indicates a positive insignificant impact in model 3 and negative insignificant impact in model 4 (model 3 β_2 – master: 0.023; model 4 β_2 – master: -0.091; $p > 0.1$). Lastly having a PhD title compared to a master's degree unveils a positive and significant influence on funding (model 3 β_2 – PhD: 0.349; $p < 0.05$; model 4 β_2 – PhD: 0.373; $p < 0.01$). In conclusion hypothesis 2a cannot be unambiguously supported with the help of models 3 and 4 either. On the one hand, compared to founders who do not have a degree, founder holding a bachelor degree raise less capital. On the other hand, founders holding a PhD raise more capital compared to founders with master

degrees.[9] Furthermore, a consistent picture can be noticed with respect to the top tier university variable in models 3 and 4. The coefficient has a positive and significant influence (model 3: $\beta_3 = 0.220$; $p < 0.05$; model 4: $\beta_3 = 0.214$; $p < 0.1$). As already suggested for model 2, this indicates that hypothesis 2b can be supported. Furthermore model 3 and 4 provide negative coefficients for founding experience (model 3: $\beta_4 = -0.127$; model 4: $\beta_4 = 0.021$; $p > 0.1$). However, these coefficients are insignificant and therefore are not sufficient to support hypothesis 3a. Consistent with models 1 and 2, a positive relationship can be established between funding and industry experience. Both coefficients are significant (model 3: $\beta_5 = 0.278$; $p < 0.01$; model 4: $\beta_5 = 0.202$; $p < 0.1$). Since the dependent variable is log-transformed and industry experience codified as dummy variable this means that the percentage change in the dependent variable is $100 * (e^{\beta n} - 1)$ according to Halvorsen and Palmquist (1980). In the case of model 3, founder having industry experience increase funding by approx. 32% and in the case of model 4 by 22%. Regarding β_6, there is again no significant impact on the dependent variable funding (model 3: $\beta_6 = 0.129$; model 4: $\beta_6 = 0.105$; $p > 0.1$). Accordingly, this again is not sufficient to find support for hypothesis 3c.

5. Discussion and conclusion

5.1. Interpretation of results

The goal of this paper was to further contribute to the research on the topic of how the background of start-up founders influences venture capital success. As described in the literature review, there are different results as to whether the factors used in this paper play a role. The type of success in venture capital is also defined differently. Herein the amount of capital raised was used. This paper expected a positive relationship with funding amount for all

[9] Since the variable top tier university could influence the education effect, all four models were also run without this variable. Furthermore, it was also regressed with a dataset that excludes the small proportion of founders who do not have an academic degree ('no degree'). These two additional specifications were performed to check whether the education effects change. However, these regressions do not yield different effects. The analyses can be found in table 9 to table 13 in the appendix.

variables present, gender (male), education, and professional experience. Table 14 in the appendix shows an overview of all hypotheses with associated expectations and results.

The first hypothesis suggested a positive relationship between being a male founder with the level of funding. The results of the analysis are not sufficient to support the hypothesis. In all four models, no significant coefficient can be identified and thus no conclusion can be drawn as to whether men raise more funding than women as suggested by the analysis of Demartini (2018) and Geiger (2020). A potential reason for the insignificant results could be the imbalance of the data set. The number of men clearly outweighs the number of women and accordingly too few data points to conclude a significant difference on average. The second hypothesis proposed that with increasing levels of education, the funding amount increases. The results of this paper do not show consistent results. On the one hand, increasing the educational level from no degree to bachelor's degree reduces the variable funding. A possible explanation for this effect could be that with a higher level of education, the time spent at university is correspondingly longer, which in turn reduces the time spent on professional experience. Since these experiences are dummy variables, this effect cannot be captured in this model. On the other hand, increasing the educational level from master to PhD increased the funding. Therefore, it can be said that a higher level of education is not simultaneously associated with a higher funding, thus hypothesis 2a cannot be supported over all education levels. Thus, the results are only partially in line with the previous literature of Ratzinger et al. (2018) and Franco et al. (2021). The related hypothesis 2b suggested a positive correlation between a top tier university and the funding amount. Models 2, 3, and 4 support the hypothesis, indicating that attending a top tier university increases funding on average. Thus, in the context of this paper, a relationship between the academic institution and the funding amount could be established. As suggested in the literature review by Nann et al. (2010), this could also have a positive impact in Germany due to the strong network effects. Contrary to the expectation that

experienced founders raise more capital, hypothesis 3a cannot be supported using model 1 and thus states that serial founders do not raise more money. This contradicts the results of Zhang (2011) who found a positive relationship between experienced founders and both capital access and amount. The study of Zhang (2011) uses a sample of venture-backed companies from the USA, which could possibly be reason for this difference. Europeans and especially Germans are known to be more risk averse than Americans, which in turn means that several foundations could be more likely to be associated with failed start-ups by venture capitalists. The test of hypothesis 3b, which suggested that founders with industry experience raise more capital on average, confirmed expectations. The result shows that a positively significant coefficient can be identified throughout all four models and can thus be supported by all models. This is consistent and even complements the findings of Siegel et al. (1993), Cooper (1994), and Grilli et al. (2020) who find a positive correlation between industry experienced founders and venture performance. In contrast, the presence of tech experience in the context of hypothesis 3c cannot be supported, as no significant results are available. In summary, it can be said that the research question was partially answered.

5.2. Limitations and future research

As with many studies, this one is not without limitations, but they also offer potential for future research. First, the quality of the data: Crunchbase, is a crowdsource-based database that generates its data through several channels, such as its community, partners, and its own experts. As mentioned in chapter 3, this source can be considered reliable, but certain errors in the data cannot be completely excluded. In this context, it should also be noted that although Crunchbase lists closed start-ups, these represented a fraction of this sample. As already mentioned during the sample construction, this could lead to a survivor bias. For the most part, only start-ups that have already managed to obtain venture capital funding are included in the data, and not start-ups and founders that have tried and failed to obtain it. Furthermore, the

website LinkedIn where especially the data for the independent variables were hand-collected, only information is published that the profile owners themselves publish. Hence, also this data quality can be doubted. However, it cannot be assumed that LinkedIn profiles, especially those of founders of young start-ups, contain untruths as this could cost both the founder and the start-up credibility in the eyes of potential investors. Another factor that limits the potential of the analysis is the use of THE ranking for the top tier university classification. Not only the already mentioned extremely heterogeneous factors play a role in these rankings, but also the lack of private business schools. Many successful start-up founders are educated at these universities, which are not considered top tier university in this paper. Furthermore, only the university of the highest degree was documented. Hence, if a bachelor's degree was obtained from a top tier university, but the master's degree was not, then this does not count as a top tier university founder in this model. Finally, the entire composition of the founding team also plays a role, which was completely excluded from this analysis. Firstly, because the founder was considered individually and not the founding team with its heterogeneity. Secondly, the funding amount collected by one start-up was allocated to all start-up founders individually. The venture capital investors usually do not decide in favor of a single person in the founding team, but rather for the team and its entire capabilities.

Last of all, a few thoughts are offered on possible future research. Firstly, within publicly accessible databases often include only successfully completed venture capital fundings. This leads to the fact that only founders are considered who were successful in the venture capital funding process. Therefore, it would be interesting to check whether such a picture can also be derived from data that also includes start-ups and founders that have not received funding. This would allow the analysis to be based on a significantly larger population. Furthermore, it would be interesting to investigate to what extent the heterogeneity of the founding team, both professionally and gender-wise, influences venture capital success.

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Appendix

Figures

Figure 1: Overview sample construction

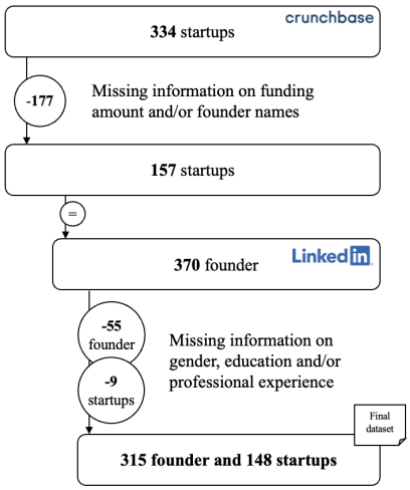


Figure 2: Outlier detection

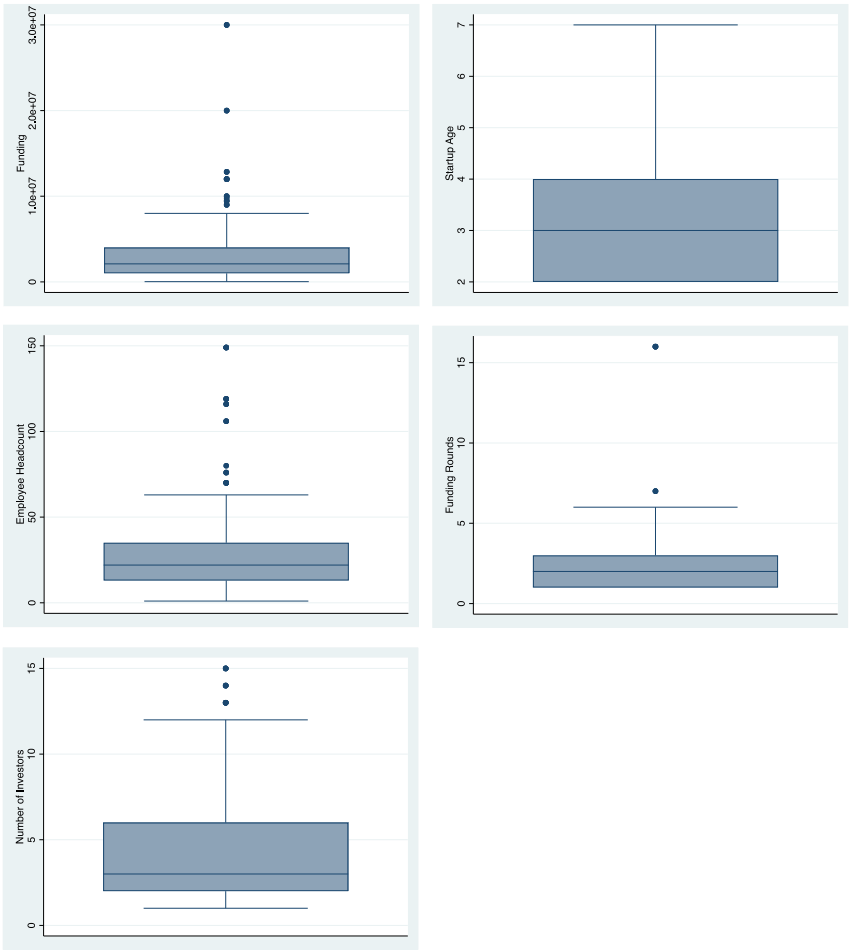


Figure 3: Distribution of variables

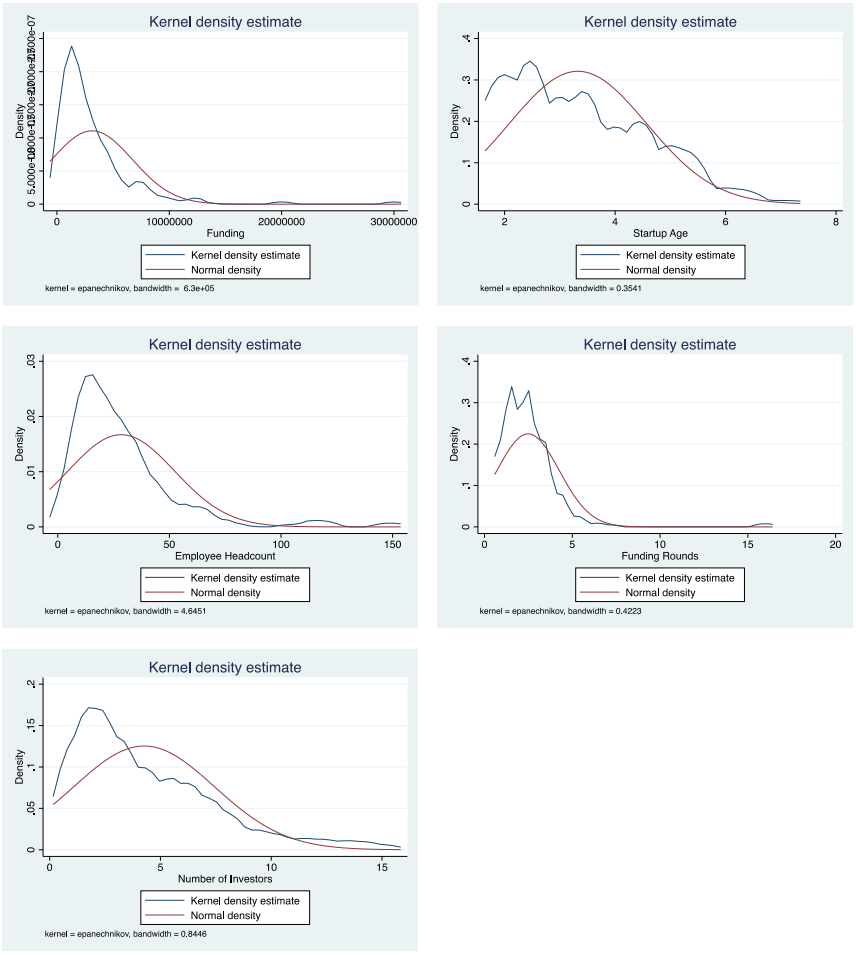
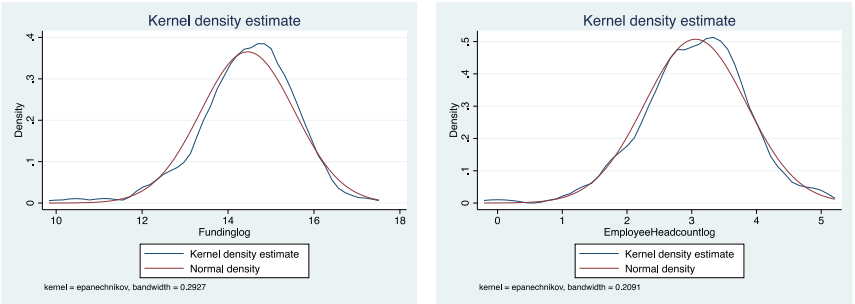


Figure 4: Log transformed variables



Tables

Table 1: Overview top tier universities of the countries that appear in the data set

Country	Ranked universities
Australia	University of Melbourne, University of Sidney, Australian National University, Australian National University, Monash University, UNSW Sydney, University of Adelaide, The University of Western Australia, University of Technology Sydney, University of Canberra, Queensland University of Technology, Macquarie University, Curtin University, Griffith University, James Cook University
Denmark	University of Copenhagen, Aarhus University, Technical University of Denmark, Aalborg University, Copenhagen Business School, University of Southern Denmark, Roskilde University
Estonia	University of Tartu, Tallinn University, Tallinn University of Technology
Finland	University of Helsinki, Aalto University, University of Oulu, Tampere University, Lappeenranta-Lahti University of Technology LUT, University of Turku, University of Eastern Finland, University of Jyväskylä, Åbo Akademi University
France	Paris Sciences et Lettres – PSL Research University Paris, École Polytechnique, Sorbonne University, Université Paris Cité, Paris-Saclay University, Télécom Paris, École des Ponts Paris Tech, École Normale Supérieure de Lyon, Montpellier University, Aix-Marseille University, Grenoble Alpes University, IMT Atlantique, Université de Versailles Saint-Quentin-en-Yvelines, University of Bordeaux, Centrale Nantes
Germany	LMU Munich, Technical University of Munich, Heidelberg University, Charite Berlin, University of Tuebingen, Humboldt University of Berlin, University of Freiburg, RWTH Aachen, University of Bonn, Free University of Berlin, University of Goettingen, University of Hamburg, University of Mannheim, Technical University of Berlin, Ulm University
Ireland	Trinity College Dublin, RCSI University of Medicine and Health Sciences, University College Dublin, University of Galway – Ollscoil na Gaillimhe, University College Cork, Maynooth University, Dublin City University, University of Limerick, Technological University Dublin
Israel	Tel Aviv University, Hebrew University of Jerusalem, Technion Israel Institute of Technology, Bar-Ilan University, University of Haifa, Reichman University, Ariel University
Italy	University of Bologna, Sant'Anna School of Advanced Studies – Pisa, Scuola Normale Superiore di Pisa, Scuola Normale Superiore di Pisa, Sapienza University of Rome, University of Padua, Vita-Salute San Raffaele University, University of Trento, University of Milan, University of Milan-Bicocca, Politecnico di Milano, University of Bari Aldo Moro, University of Brescia, University of Florence, Free University of Bozen-Bolzano
Latvia	University of Latvia, Latvia University of Life Sciences and Technologies, Riga Technical University
Netherlands	Wageningen University & Research, University of Amsterdam, Leiden University, Erasmus University Rotterdam, Utrecht University, Delft University of Technology, University of Groningen, Vrije Universiteit Amsterdam, Maastricht University, Radboud University, Eindhoven University of Technology, Tilburg University, University of Twente
New Zealand	University of Auckland, University of Otago, Auckland University of Technology, University of Canterbury, Victoria University of Wellington, University of Waikato, Lincoln University, Massey University
Portugal	Catholic University of Portugal, NOVA University of Lisbon, University of Porto, University of Lisbon, University of Alveiro, University of Beira Interior, University of Coimbra, ISCTE-University Institute of Lisbon, University of Algarve, University of Minho, Polytechnic Institute of Porto, University of Trás-os-Montes and Alto Douro
Spain	Pompeu Fabra University, Autonomous University of Barcelona, University of Barcelona, University of Navarra, Autonomous University of Madrid, CEU Universities, University of Valencia, Complutense University of Madrid, University of the Balearic Islands, University of Deusto, European University of Madrid, University of Girona, University of Granada, Universitat Internacional de Catalunya, Jaume I University
Sweden	Karolinska Institute, Lund University, Uppsala University, Stockholm University, University of Gothenburg, Chalmers University of Technology, KTH Royal Insitute, Oerbro University, Swedish University of Agricultural Sciences, Umeå University, Linköping University, Karlstad University

Switzerland	ETH Zurich, École Polytechnique Fédérale de Lausanne, University of Zurich, University of Basel, University of Bern, University of Geneva, University of Lusanne, Università della Svizzera italiana, University of Fribourg, University of Neuchâtel, University of St Gallen
United Kingdom	University of Oxford, University of Cambridge, Imperial College London, University College London, London School of Economics and Political Science, University of Edinburgh, Kings College London, University of Manchester, University of Warwick, University of Bristol, University of Glasgow, University of Birmingham, Queen Mary University of London, University of Sheffield, University of Southampton
USA	Stanford University, Harvard University, California Institute of Technology, Massachusetts Institute of Technology, University of California, Berkeley, Yale University, Princeton University, The University of Chicago, Johns Hopkins University, University of Pennsylvania, University of California, Los Angeles, Columbia University, Cornell University, University of Michigan-Ann Arbor, Northwestern University
Source: https://www.timeshighereducation.com/world-university-rankings/2021/world-ranking	

Table 2: Overview of the data collection of the founders' biographies

Name	Definition
Gender	German names well distinguishable in gender, if this was not the case, the gender could be clearly identified with the help of the LinkedIn profile picture or from name databases
Education	- No Degree: no entry in LinkedIn of higher education, apprenticeship, or high school diploma - Bachelor: Bachelor of Science, Bachelor of Arts, Bachelor of Laws, Bachelor of Engineering, Bachelor of Education - Master: Master of Science, Master of Arts, Master of Laws, Master of Engineering, Bachelor of Education, all types of MBAs, and the German 'Diplom' - PhD: Doctoral, Doctorate, PhD Candidate
Founding Experience	Keywords: Founder, Co-Founder, Serial Founder, Entrepreneur
Tech Experience	Keywords: Developer, ERP admin, tech programmer, full-stack developer, research assistant in computer science, software engineer, technology scientist, R&D, CTO

Table 3: Overview of variables

Name	Definition
Funding	Continuous variable represents funding amount in euro by start-up at seed round
Gender	Dichotomous variable takes value one if founders' gender is male and zero if female
Education	Set of four dummy variables: 'No degree' (takes value one if founder cannot present academic degree else zero); 'Bachelor' (takes value one if founders' highest degree is a bachelor's degree else zero); 'Master' (takes value one if founders' highest degree is a master's incl. 'Diplom' & 'MBA' degree else zero); 'PhD' (takes value one if founders' highest degree is a PhD degree else zero)
Top Tier University	Dichotomous variable takes value one if founder's highest comes from a top tier university else zero
Founding Experience	Dichotomous variable takes value one if founder has ever founded a start-up before else zero
Industry Experience	Dichotomous variable takes one if founder has experience in the same industry as start-up operates else zero
Tech Experience	Dichotomous variable takes one if founder has tech-related experience else zero
Software	Dichotomous variable takes value one if the founder's start-up works with software else zero
Start-up Age	Ordinal discrete variable representing the time between foundation and the funding date

Employee Headcount	Ordinal discrete variable representing the number of the start-up employees
Funding Rounds	Ordinal discrete variable representing the total number of funding rounds that the start-up performed (incl. debt financing)
Number of Investors	Ordinal discrete variable representing the number of existing investors
State	Set of 15 dummies representing German states where the start-ups operate: Baden Wuerttemberg, Bavaria, Berlin, Brandenburg, Bremen, Hamburg, Hesse, Lower Saxony, Mecklenburg-West Pomerania, North-Rhine Westphalia, Rhineland Palatinate, Saarland, Saxony, Schleswig-Holstein, Thuringia
Industry	Set of 20 dummies representing industries of the dataset: Biotechnology, Commerce and Shopping, Community and Lifestyle, Consumer Goods, Energy, Financial Services, Food and Beverage, Hardware, Health Care, Information Technology, Insurance, Legal, Manufacturing and Construction, Media and Entertainment, Robotic and Artificial Intelligence, Sales and Marketing, Science and Engineering, Services, Transportation, Travel and Tourism
Funding Date	Set of 21 dummies representing of funding period between January 2021 and September 2022

Table 4: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Funding	315	3,129,073	3,604,991	25,000	30,000,000
Gender	315	0.848	0.360	0	1
Education					
No Degree	315	0.041	0.199	0	1
Bachelor	315	0.254	0.436	0	1
Master	315	0.537	0.499	0	1
PhD	315	0.168	0.375	0	1
Top tier University	315	0.333	0.472	0	1
Founding Experience	315	0.359	0.48	0	1
Industry Experience	315	0.337	0.473	0	1
Tech Experience	315	0.273	0.446	0	1
Software	315	0.698	0.460	0	1
Start-up Age	315	3.327	1.243	2	7
Employee Headcount	315	28.416	23.888	1	149
Funding Rounds	315	2.483	1.776	1	16
Number of Investors	315	4.263	3.184	1	15

Table 5: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Funding	1.000													
(2) Gender	-0.114*	1.000												
(3) Bachelor	0.003	0.044	1.000											
(4) Master	-0.059	-0.040	-0.628*	1.000										
(5) PhD	0.067	0.002	-0.262*	-0.484*	1.000									
(6) Top tier University	0.102	-0.150*	-0.150*	0.077	0.150*	1.000								
(7) Founding Experience	-0.127*	0.041	0.081	-0.035	-0.018	-0.051	1.000							
(8) Industry Experience	0.111*	0.022	-0.184*	0.002	0.147*	-0.033	0.112*	1.000						
(9) Tech Experience	-0.006	0.181*	0.101	-0.159*	-0.009	-0.055	0.077	-0.059	1.000					
(10) Software	-0.118*	0.087	0.097	-0.028	-0.074	-0.005	0.073	-0.044	0.201*	1.000				
(11) Start-up Age	0.076	0.019	0.028	-0.073	0.052	-0.040	0.000	-0.058	0.011	-0.078	1.000			
(12) Employee Headcount	0.411*	-0.091	0.074	-0.019	-0.019	0.119*	-0.022	-0.007	-0.034	-0.164*	0.146*	1.000		
(13) Funding Rounds	-0.012	-0.054	0.072	-0.059	0.016	0.108	-0.054	-0.020	-0.002	-0.040	0.318*	0.024	1.000	
(14) Number of Investors	0.246*	-0.090	0.046	0.083	-0.157*	-0.031	-0.062	-0.029	-0.046	-0.020	0.011	0.277*	0.277*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Regression table; reference group no degree

	Model 1	Model 2	Model 3	Model 4
Dependent Variable	Funding Amount	Funding Amount	Funding Amount (log)	Funding Amount (log)
Gender	-677,786 (520,032)	-300,846 (500,848)	-0.198 (0.137)	-0.133 (0.140)
Education				
Bachelor	-100,721 (1,003,883)	-647,414 (944,361)	-0.508* (0.264)	-0.511* (0.264)
Master	-511,520 (968,880)	-1,205,380 (916,357)	-0.485* (0.254)	-0.603** (0.256)
PhD	272,686 (1,033,682)	-715,089 (969,224)	-0.136 (0.272)	-0.23 (0.272)
Top tier University	559,454 (408,968)	936,548** (407,670)	0.22** (0.108)	0.214* (0.114)
Founding Experience	-926,006** (384,622)	-343,679 (369,691)	-0.127 (0.101)	0.021 (0.103)
Industry Experience	1,009,288** (400,287)	813,072** (392,905)	0.278*** (0.105)	0.202* (0.110)
Tech Experience	376,215 (433,738)	201,066 (389,890)	0.129 (0.114)	0.105 (0.109)
Software	-367,439 (411,476)	218,121 (473,807)	-0.035 (0.107)	0.021 (0.132)
Start-up Age	182,340 (158,201)	-259,566 (176,959)	0.084** (0.041)	0.013 (0.050)
Employee Headcount / (log)	49,703*** (8,296)	41,389*** (9,667)	0.707*** (0.066)	0.725*** (0.083)
Funding Rounds	-230,242** (115,106)	-156,134 (114,377)	-0.130*** (0.030)	-0.139*** (0.032)
Number of Investors	215,395*** (63,519)	152,578** (75,508)	0.062*** (0.017)	0.040* (0.021)
Constant	1,551,943 (1,221,148)	7,605,914*** (2,325,404)	12.523*** (0.357)	13.574*** (0.670)
State	Not included	Included	Not included	Included
Industry	Not included	Included	Not included	Included
Funding Date	Not included	Included	Not included	Included
Observations	315	315	315	315
R-Squared	0.245	0.568	0.433	0.632
Prob > F	0.000	0.000	0.000	0.000

**** p<0.01; ** p<0.05; * p <0.10*
(Standard errors in parentheses)

Table 7: Regression table; reference group bachelor

	Model 1	Model 2	Model 3	Model 4
Education				
No Degree	100,721 (1,003,883)	647,414 (944,361)	0.508* (0.264)	0.511* (0.264)
Master	-410,799 (452,432)	-557,966 (427,842)	0.023 (0.119)	-0.091 (0.120)
PhD	373,407 (602,994)	-67,674 (598,812)	0.373** (0.158)	0.281* (0.168)
Constant	1,451,222 (914,056)	6,958,500*** (2,158,346)	12.014*** (0.301)	13.062*** (0.632)

**** p<0.01; ** p<0.05; * p <0.10*
(Standard errors in parentheses)
The rest of the table is not shown because coefficients of other variables do not change when the reference group of education is exchanged. This also applies to the following table 8.

Table 8: Regression table; reference group master

	Model 1	Model 2	Model 3	Model 4
Education				
No Degree	511,520 (968,880)	1,205,380 (916,357)	0.485* (0.254)	0.603** (0.256)
Bachelor	410,799 (452,432)	557,966 (427,842)	-0.023 (0.119)	0.091 (0.120)
PhD	784,206 (519,438)	490,291 (502,309)	0.349** (0.137)	0.373*** (0.141)
Constant	1,040,423 (850,953)	6,400,534*** (2,180,596)	12.038*** (0.280)	12.971*** (0.636)

**** p<0.01; ** p<0.05; * p <0.10*
(Standard errors in parentheses)

Table 9: Regression table without top tier university variable; reference group no degree

	Model 1	Model 2	Model 3	Model 4
Dependent Variable	Funding Amount	Funding Amount	Funding Amount (log)	Funding Amount (log)
Gender	-772,813 (516,114)	-392,044 (503,541)	-0.234 (0.136)	-0.155 (0.140)
Education				
Bachelor	-24,314 (1,003,773)	-445,819 (948,316)	-0.480* (0.265)	-0.463* (0.264)
Master	-335,789 (961,710)	-835,046 (909,778)	-0.416 (0.253)	-0.516** (0.253)
PhD	515,166 (1,019,838)	-281,062 (958,758)	-0.044 (0.270)	-0.130 (0.268)
Founding Experience	-942,710** (384,983)	-362,110 (372,764)	-0.133 (0.102)	0.018 (0.104)
Industry Experience	976,963** (400,164)	757,859* (395,522)	0.264** (0.106)	0.189* (0.110)
Tech Experience	377,135 (434,363)	171,013 (393,003)	0.127 (0.115)	0.098 (0.110)
Software	-338,226 (411,514)	293,503 (476,711)	-0.028 (0.107)	0.033 (0.132)
Start-up Age	159,049 (157,509)	-278,456 (178,280)	0.077* (0.041)	0.010 (0.050)
Employee Headcount / (log)	51,496*** (8,203)	44,323*** (9,664)	0.730*** (0.065)	0.742*** (0.083)
Funding Rounds	-205,323* (113,820)	-120,691 (114,301)	-0.121*** (0.030)	-0.131*** (0.032)
Number of Investors	205,888*** (63,229)	111,596 (73,997)	0.058*** (0.017)	0.031 (0.020)
Constant	1,665,908 (1,220,059)	8,089,822*** (2,335,647)	12.517*** (0.358)	13.642*** (0.673)
State	Not included	Included	Not included	Included
Industry	Not included	Included	Not included	Included
Funding Date	Not included	Included	Not included	Included
Observations	315	315	315	315
R-Squared	0.241	0.559	0.426	0.627
Prob > F	0.000	0.000	0.000	0.000

**** p<0.01; ** p<0.05; * p <0.10*
(Standard errors in parentheses)

Table 10: Regression table without top tier university variable; reference group bachelor

	Model 1	Model 2	Model 3	Model 4
Education				
No Degree	24,314 (1,003,773)	445,819 (948,316)	0.480* (0.265)	0.463* (0.264)
Master	-311,475 (447,211)	-389,226 (425,094)	0.063 (0.118)	-0.053 (0.118)
PhD	539,480 (591,498)	164,757 (595,249)	0.436*** (0.156)	0.333** (0.166)
Constant	1,641,595* (904,703)	7,644,003*** (2,155,897)	12.038*** (0.302)	13.180*** (0.632)

**** p<0.01; ** p<0.05; * p <0.10*
(Standard errors in parentheses)
The rest of the table is not shown because coefficients of other variables do not change when the reference group of education is exchanged. This also applies to the following table 11.

Table 11: Regression table without top tier university variable; reference group master

	Model 1	Model 2	Model 3	Model 4
Education				
No Degree	335,789 (961,710)	835,046 (909,778)	0.416 (0.253)	0.516** (0.253)
Bachelor	311,475 (447,211)	389,226 (425,094)	-0.063 (0.118)	0.053 (0.118)
PhD	850,955 (517,886)	553,984 (505,833)	0.373*** (0.137)	0.386*** (0.142)
Constant	1,330,120 (825368.55)	7,254,776*** (2,167,028)	12.101*** (0.280)	13.126*** (0.634)

**** p<0.01; ** p<0.05; * p <0.10*
(Standard errors in parentheses)

Table 12: Regression table without no degree founders; reference group bachelor

	Model 1	Model 2	Model 3	Model 4
Dependent Variable	Funding Amount	Funding Amount	Funding Amount (log)	Funding Amount (log)
Gender	-690,492 (539,231)	-263,948 (517,262)	-0.200 (0.142)	-0.113 (0.140)
Education				
Master	-434,664 (459,449)	-566,258 (433,811)	0.019 (0.121)	-0.097 (0.117)
PhD	347,553 (612,501)	-60,629 (609,208)	0.37** (0.161)	0.306* (0.165)
Top tier University	561,532 (415,865)	841,956** (416,319)	0.216** (0.110)	0.170 (0.112)
Founding Experience	-971,133** (397,830)	-449,026 (377,793)	-0.134 (0.105)	-0.025 (0.102)
Industry Experience	1,011,924** (416,477)	717,629* (412,134)	0.271** (0.110)	0.144 (0.112)
Tech Experience	264,815 (452,290)	-8,850 (408,402)	0.090 (0.119)	-0.009 (0.110)
Software	-334,467 (428,216)	345,522 (487,906)	-0.03 (0.111)	0.095 (0.131)
Start-up Age	177,904 (164,299)	-272,676 (186,334)	0.078* (0.042)	-0.005 (0.051)
Employee Headcount / (log)	49,002*** (8,493)	44,195*** (9,927)	0.712*** (0.068)	0.758*** (0.083)
Funding Rounds	-239,287** (117,729)	-128,755 (118,819)	-0.130*** (0.031)	-0.130*** (0.032)
Number of Investors	206,644*** (65,842)	119,110 (79,062)	0.059*** (0.017)	0.026 (0.021)
Constant	1,594,983* (949,297)	6,895,397*** (2,256,528)	12.05*** (0.309)	13.044*** (0.638)
State	Not included	Included	Not included	Included
Industry	Not included	Included	Not included	Included
Funding Date	Not included	Included	Not included	Included
Observations	302	302	302	302
R-Squared	0.240	0.572	0.428	0.658
Prob > F	0.000	0.000	0.000	0.000

**** p<0.01; ** p<0.05; * p <0.10*
(Standard errors in parentheses)

Table 13: Regression table without no degree founders; reference group master

	Model 1	Model 2	Model 3	Model 4
Education				
Bachelor	434,664 (459,449)	566,258 (433,811)	-0.019 (0.121)	0.097 (0.117)
PhD	782,217 (527,283)	505,630 (512,077)	0.350** (0.139)	0.403*** (0.139)
Constant	1,160,319 (886,305)	6,329,138*** (2,281,306)	12.069*** (0.288)	12.947*** (0.643)

**** p<0.01; ** p<0.05; * p <0.10*
(Standard errors in parentheses)

Table 14: Summary of hypothesis

Hypothesis		Model 1	Model 2	Model 3	Model 4
1) Gender (male)	↑	—	—	—	—
2a) Education	↑	—	—	✓/✗	✓/✗
2b) Top tier University	↑	—	✓	✓	✓
3a) Founding experience	↑	✗	—	—	—
3b) Industry experience	↑	✓	✓	✓	✓
3c) Tech experience	↑	—	—	—	—

↑ positive relationship ✓ significant support ✗ significant opposite support — no significant support