TEAM ATTRIBUTES AND INVESTOR ATTRACTIVENESS

THE RELATIONSHIP BETWEEN FOUNDER CHARACTERISTICS AND STARTUP FUNDING

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Team Attributes and Investor Attractiveness: The Relationship Between Founder Characteristics and Startup Funding

Abstract:

This paper examines the relationship between professional experience, education and gender diversity of startup founding teams and funding raised. Intuitively, experience and education should have a positive impact on funding in early companies as the founding team is a crucial part of the investment decision for early investors. Data from 317 companies in the information and technology industry based in the Nordic countries and their 675 founders show that while characteristics such as business education, managerial experience and previous founding experience positively impacted the amount of funding a company raised, characteristics such as engineering degrees, software development experience and PhDs did not show a significant relationship. Gender diversity negatively impacted funding raised. The impact of these characteristics did not get weaker between the first and subsequent funding rounds, instead the correlations became stronger, indicating that the importance of founder characteristics is not diminished with time even though more financial data becomes available.

Keywords:

Startup funding, startup founders, Early stage investing, Entrepreneurship, Venture Capital

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1. Introduction

Entrepreneurs, investors and researchers have long argued and discussed the importance of founding team characteristics in the entrepreneurial process such as previous entrepreneurial success (e.g., Gompers et al, 2006) and competence in the field of endeavour (e.g., Khan, 1986). While it is intuitive that previous success and competency of the founding team in the field of endeavour will affect a startup's success, research in this area is lacking as tangible connections between founder characteristics and financial outcomes have been difficult to quantify. This thesis quantifies these connections and finds that startup founder characteristics impact funding. Specifically, a connection between the composition of background characteristics and experience in the founding team to the amount of investment funding their companies raise. The thesis also investigates whether this connection gradually fades with time when more financial information becomes available.

While funding is not the same as success for a company the two are closely linked and often interchanged in media and literature as few things are as crucial as capital to early stage companies increasing their growth, success and survival rate (Lerner, et al. 2018). The quest for capital is therefore a hotly debated topic among entrepreneurs and while the industry has changed remarkably in the last decade and set earth-shattering records for early stage funding, the basics still remain the same (Teare, 2020). Investors must base decisions and due diligence on two main factors, business model and team characteristics as classic quantitative analysis of results, cash flow and balance sheet are nigh meaningless to determine potential for early stage companies.

A relationship between founder characteristics and funding amount should exist for several reasons. Firstly, founders with characteristics such as degrees in business or engineering as well as experience in founding companies and company leadership bring valuable resources to early stage companies, Secondly, it provides a basis for investors to evaluate the company which is crucial without substantial financial data (Beaton, 2013).

Although these relationships are intuitive, systematic research is lacking. Early stage investments are by nature almost always private and specific transaction data and standardised founder characteristics are difficult to obtain. Researchers have historically relied on self-reported data which limit generalisability and of which the accuracy suffers from aggrandisement by respondents. (Hoang & Antoncic, 2003, Hoang & Yi, 2015).

This thesis aims to empirically assess if startup founder characteristics have a statistically significant relationship with equity funding raised. To accomplish this, the company network Crunchbase.com was used to identify early stage companies who raised funding in the last decade and their respective founders. Characteristics of these founders were then gathered on LinkedIn.com. Though studies suggest that globalization of angel investment is increasing this study used data on companies within the information and technology sector that were located in the Nordic countries Sweden, Finland, Norway and Denmark to increase population size while maintaining comparable financial systems (Hyytinen & Pajarinen, 2001).

Modern sites such as professional networking site LinkedIn.com and startup database network sites like Crunchbase.com provide detailed information on early stage companies and their founders, allowing individual classification and categorisation of founder characteristics as well as data on each round of capital raised. This access provides a rich data source that can be used to analyse the relationship between founder characteristics and funding amount.

1.1 Thesis Focus

The thesis focuses on the early investment rounds (up to and including Series A). Establishing connections between founder characteristics and early funding amounts would be valuable as it gives stakeholders in the startup funding scene such as venture capitalists, angel investors and founders an overview of which characteristics that statistically seem valuable and therefore possibly guide the investment decision-making process.

The amount of equity sold in seed and Series A rounds differs but usually 10 - 15% of equity is sold in a seed round and usually 25 - 35% for a Series A round (Henry, 2016). This difference in equity is important to take into account since it influences the amount of money raised. If possible to obtain, the pre-money valuation at the time of the investment would be a better independent variable to track but unfortunately pre-money valuations are not publicly disclosed in the same way that money raised is and therefore much harder to access.

To further standardise the amount of funding required by companies, the thesis scope is companies in the information and technology (IT) industry. Including companies that mainly provide physical products would have led to a larger variation in capital requirement since these companies typically need funds for production and often a larger workforce (Mitroff, 2012). The capital requirement within the information and technology sector varies as well but is more standardised than if additional industries had been included. An information and technology company is in this thesis defined as a company that provides some kind of web service, app or other service that requires software development and does not produce physical goods as their main product. The service itself may in some cases facilitate the exchange of physical products but these are then not produced by the company itself.

The thesis is structured in order to answer two main research questions and associated sub research questions:

1. Do founder characteristics impact the amount of equity funding early stage companies raise?
    a. Does founder education impact funding?
    b. Does founder professional experience impact funding?
    c. Does founder team gender diversity impact funding?
2. Are team characteristics a better predictor of first round funding than of total funding raised in subsequent rounds?

2. Background

Intuitively, characteristics such as professional experience and education should positively impact the amount of funding that founders of a company are able to raise for their venture. Although variation exists in each category, investment into young companies is usually standardized into a set of rounds, each with specific characteristics. The first category of funding is called pre-seed funding (sometimes called friends and family funding) in which a company raises a small amount of money from people they have a relation to as well as invest in the company personally to provide initial capital.

The first funding rounds in a start-up company (outside of friends and family investments) are called seed-rounds. Investors in these rounds are traditionally angel investors but especially in tech it is also common with venture capital firms (VCs) among the investors. A company can take several rounds of seed funding. The amount of money raised in a seed round varies but one round usually raises somewhere between 10 000 - 1 000 000 dollars and the average equity stake sold is around 10 - 15%. The next founding stage is called Series A and constitutes a larger investment that usually comes when the company has a proven business model and reliable revenue. In these rounds the main investors are VCs but other investors may take part as well. In a series A round usually about 25 - 35% of equity is sold. After this round the company can take funding in additional rounds that are then called series B, C, D etc. (Henry, 2016).

2.1 Information and technology companies

Companies analyzed in this thesis all provide a software service as their main product or provide services to help other companies create software solutions. Software services can be apps, websites or software installed on computers and/or phones. This was achieved by segmenting companies listed on Crunchbase.com. A small number of companies that provide both software services and physical products may be included in the data set since companies diversify over time and specific activities of each company have not been examined manually.

2.2 Early stage startups

All companies in the data set have received some form of equity funding. In order to standardize company stages the thesis only includes only early stage startups which are defined as companies that have received funding up to and including series A. Later stages could have been included but this would have led to a greater variation in the data and the companies would have been more established and more similar to mature companies.

2.3 Crunchbase - database of company funding

Crunchbase (crunchbase.com) is a commercial directory on innovative companies and has become the most important resource for data in the tech/startup world (Organisation for Economic Co-operation and Development [OECD], 2018).

> "Breschi, Lassébie and Menon (2018) discuss the coverage of the database, compared to some benchmark data sources that are more commonly used in the literature. The general message of the benchmarking exercise that Crunchbase has a better coverage of VC deals and start-ups than comparable data sources. The country-year comparison with aggregated sources on VC investments also suggests that the coverage of Crunchbase is sufficiently exhaustive across OECD member countries... " (OECD, 2018, p. 289)

The access to self-reported digital directories like Crunchbase.com gives researchers unprecedented insight into connections between companies, founders and financial data. This information, as it is private by nature, has previously been difficult to obtain and many previous studies have had to rely on company contacts and small scale surveys to estimate population trends (Hsu, 2007).

2.4 LinkedIn - individual founder characteristics

Launched in 2003, LinkedIn (www.linkedin.com) has become the world's primary professional social network with 690 million members worldwide (LinkedIn, 2020). Essentially an online resume, the site today is a key tool for employers searching for prospective employees with some studies suggesting that more than 70% of companies rely on LinkedIn to evaluate which applicants to invite for an interview (Caers & Castelyns, 2011). It is equally important for employees looking for employment or keeping contact with professional peers and interesting companies.

The site publicly provides the educational and professional background of members, allowing for gathering of company founder characteristics. Although resumes are subject to some embellishment, Guillory and Hancock (2012) showed that people are less likely to lie about their accomplishments online than in private resumes.

Numerous earlier studies used LinkedIn and Crunchbase for data gathering. An example of this is the work of Banerji and Reimer (2019) in which financial data from Crunchbase and founder data from LinkedIn was used to find a relationship between social connectedness and entrepreneurial success.

3. Previous Literature

The science of what makes a successful entrepreneurial team is an area of great interest for different business specializations but systematic quantitative research regarding founder qualities is still scarce. Studies on other startup characteristics can however be analogously adapted to this thesis.

3.1 Funding as dependent variable

Several studies use funding as a dependent variable in order to assess company success. Jin, Wu, and Hitt (2017) used funding in order to assess the impact of a good social media strategy for early ventures. Kanze and Lyengar (2014) used an approach similar to the one used in this thesis and examined founder qualities by gathering LinkedIn data and found that founders classifying themselves as disruptors received significantly more funding than those who described themselves as builders. A study from 2018 showed that the signalling value of a US government grant increased the likelihood for an early tech venture to close subsequent funding rounds (Islam, Fremeth & Marcus, 2018). Another study (Torrisi, Toschi & Zhang, 2014) investigated if general media coverage and other variables connected to reputation influenced the ability to receive VC-funding.

3.2 Experience

Investors focusing on early stage companies have a limited set of attributes to evaluate a company on and the lack of track record makes the investment, that also usually lack securities, very high risk. Investors have to rely on attributes that are available and observable at the time and associate them with hidden determinants of the quality of the startup. Experience is one such observable attribute and becomes an important quality (Stuart, Hoang & Hybels, 1999). Especially since it can be valuable both as a productive and quality signal (Hoenig and Henkel, 2015). Industry experience also impacts ability to realistically forecast entrepreneurial success, especially in high-tech industries (Cassar, 2014).

Experience of founding previous companies can also be used to assess the skill of a startup founder. Gompers et al. (2006) showed that entrepreneurs who have previously been successful are more likely to succeed than both entrepreneurs who have previously failed and entrepreneurs who are starting their first company. Other studies indicate that previous entrepreneurial experience is beneficial regardless of the success of previous ventures (Lafontaine & Shaw, 2016).

3.3 Gender

It is a fact that female founders are still underrepresented in the startup world, especially among tech companies. A study from 2008 estimated that 7% of founders in high tech companies are women (Brush, 2008). Though fresh data from crunchbase show that almost 20% of newly founded companies have a female founder on the team this number is still likely lower when looking only at information and technology companies. Research also suggests that VC investors may ask harder questions to women than to men and favour same sex investments. (Kanze et al., 2018).

3.4 Education

Research suggests that a university education is important for entrepreneurship and that a vast majority of founders have at least a bachelor's degree (Wadhwa et al., 2009). Wilson et al showed in an article published in 2014 that the education of the manager-owner impacts the growth rate of a firm (Wilson ,2014). There is also a body of research focusing on whether or not entrepreneurship education actually results in better entrepreneurs with varied results. An interesting study conducted in Mozambique from 2018 showed that entrepreneurship, at least in the market studied, was probably more driven by inborn personality traits than by education (Sawaya & Bhero, 2018). Other studies supporting this conclusion are Rasmussen et al. (2006) and Nagler and Naude (2014) which both argue that the link between education and entrepreneurial success is not statistically significant. However these studies all have a broad scope and their generalisability to the information and technology industry is questionable. The conclusion is that granular research on what kind of education is most important in information and technology startups is still mostly lacking.

4. Data

The data set consists of 318 information and technology companies based in the Nordic Countries (Sweden, Finland, Norway and Denmark) that have raised funding in seed rounds up until and including series A rounds and their 675 founders. The data set only includes companies founded after and including the year 2000 that have raised their first funding round in the last decade (after and including 2010). The vast majority (296) of these were also founded in the last decade. The study uses two data sets, one for individual founders and one for companies. The data from individual founders is aggregated on the company level and the data used in the regression models is on a company basis. Of these 318 companies there was one missing value on total and first equity funding which resulted in 317 companies used in the regression. The data of the main results is not adjusted for any outliers in order to properly reflect reality.

4.1 Data collection

4.1.1 Web Scraping

The company data was collected in three steps. The first step encompassed using the website CrunchBase.com, a directory of companies mainly used by startups, venture capital firms and angel investors, for collection of company related data and LinkedIn profiles of all the founders. In order to facilitate this step an application programming interface called a web scraper was used which scours and extracts certain HTML-code strings from websites.

We used the application programming interface ScraperAPI (ScraperAPI.com) and altered it to fit our purposes. The next step after collecting the individual LinkedIn links was to collect data on the individual founders.

4.1.2 Manual collection of founder data from LinkedIn

The second step was to gather founder characteristics. Though preferably done through a web scraping API as well, LinkedIn collection was done manually as the site rigorously protects itself against web scrapers. Characteristics were therefore gathered from the professional networking site LinkedIn manually by visiting each of the individual founder's pages and recording matches to predetermined characteristics. After collection the founder data was aggregated for each company.

4.1.3 Gender data collection

In order to assess team gender diversity we used an application programming interface, Gender API (Gender-API.com) which predicts the gender of a person based on first name. This function helped in automating the data classifying process.

4.1.4 Adjustments for inflation and currency

OECD data on historic exchange rates and country inflation was used to approximate the real value of each funding round in 2019 Euro value (OECD, 2020).

4.2 Company data

The data gathered from the founders was then summarized on a company basis since the aim is to investigate teams of startups and not individual founders. Additional data was also collected on a company basis. The section below states definitions of all data points collected and aggregated on a company level.

4.2.1 Team characteristics

The data regarding founder characteristics only includes characteristics achieved before starting the company included in the data set. For example when measuring the number of founders in a company that have a business degree only founders who finished their business degree before founding the company are counted as having this characteristic.

Number of founders measures how many founders a particular company has. Team gender diversity measures if the team has at least one founder of both genders. The majority of startup teams in this study consists of only males (see table 1) which means that a non-gender diverse team in most cases is a team with only males. However there are a few teams with only women in the data set as well, these teams will be coded as non-gender diverse.

4.2.2 Team experience

Data points regarding team experience are aggregated on a company level. Further definitions of specific founder characteristics can be found in section 4.3.

Average founded companies measures how many companies the founders of a company on average founded before starting the company, the one in our set, and is hence a proxy for earlier startup experience. Only companies started before the current company is included which means the current company is not counted. The data is not adjusted for the fact that founders of a specific company may have founded earlier companies together and therefore the total number of unique companies founded before in some cases is less than the data implies. However, even if the founders have earlier experience from the same company the founders still have individual startup experience.

Total number of founders with earlier company leadership positions provides data on how many founders on the team that have earlier company leadership experience. Total number of founders with software experience is the corresponding data point for software experience.

4.2.3 Team education

The following data points regarding team education are aggregated on a company level. Further definitions of the degrees can be found in 4.3.

- Total number of founders with a business degree
- Total number of founders with a technical degree
- Total number of founders with an MBA degree
- Total number of founders with a PhD degree

4.2.4 Measures of time

Years between founding and first funding round measures the number of years between the date the company was founded until it received its first funding and is calculated by subtracting the founding year from the year of the first funding. Company age quantifies how many years the company has been in business and is calculated by subtracting the founding year from the current year (2020).

4.2.5 Industry

Variables summarized below states which industry a company is in. The industries accounted for below do not cover all companies in our set but are the main niches besides pure information technology companies. All companies in our set provide some sort of software service or app as their main product and the industries listed below should therefore be seen as segments within the software industry. It is also worth noting that a company can be in more than one industry. Sectors included in the analysis are:

- Healthcare
- E-commerce
- Machine learning
- Financial services
- Advertising and marketing

4.2.6 Geographics

In order to assess differences in the startup scene between scandinavian countries country data was gathered. The data points state where the company was founded and has its HQ. Companies may still be active in other countries as well.

- Sweden
- Denmark
- Finland
- Norway

4.2.7 Equity funding

Two main data points on funding are tracked on the company level

- Total equity funding
- First equity funding

Total equity funding received quantifies how much total equity funding a company has received up to and including the series A rounds. All amounts are standardized to 2020 euros by correcting for country specific inflation and historical exchange rates.

Total amount of equity funding received in the first funding round shows how much equity funding a specific company received in its first funding round. All amounts are standardized to 2020 euros by correcting for country specific inflation and historical exchange rates. This data point will for simplicity be called first equity funding.

4.3 Founder data

The founder data consists of 8 characteristics for each founder regarding the founders education, earlier professional experience and gender. The characteristics are limited to traits a founder has achieved before the founding of the company. If a specific founder for example achieves the criteria for company leadership experience after founding the specific company in our analysis the founder will not be counted as having this trait. Ergo the characteristics are predetermined and not changeable by the dependent variables. First funding or total funding cannot affect a founders previous education, professional experience and gender. Below follows descriptions and definitions of the founder data.

4.3.1 Number of companies founded

This variable states how many companies the founder has founded before founding the specific company included in the analysis.

4.3.2 Gender

States whether the founder is male or female based on first name Gender API estimates.

4.3.3 Business degree

States if the founder has a business degree or not. Both MsC and BsC degrees in any field of specialization (finance, economics, marketing etc) are included. Shorter business programs of one year (often online based) are not included. There is no specification on which specific school a founder received the degree from.

4.3.4 Technical degree

States whether the founder has a technical degree or not. The definition of technical degree is a degree in: any type of engineering, computer science, mathematics, physics, information technology or chemistry. The main objective with this data point is to quantify if a founder has a technical academic background. It should be stated that the vast majority of founders that have a technical degree in our data set have a degree in either engineering or computer science while mathematics, physics, information technology and chemistry degrees are much more uncommon.

4.3.5 Company leadership experience

States whether the founder has had an earlier C-level or director position before founding the company or not. This data point only includes positions in companies that are non-self founded. No limitations on company size or age was imposed.

4.3.6 Software experience

States whether the founder has more than one year of experience working as a software developer or a degree in software engineering/computer science before founding the company. The reason a degree in software engineering/computer science is also included in this metric is that these degrees imply knowledge of programming. The main idea behind this variable is to quantify whether a startup team has programming skills in the founder team or not.

4.3.7 PhD degree

States if the founder has a PhD in any field before founding the company. Any type of PhD degree will be counted even though the nature of these may differ greatly between fields.

4.3.8 MBA degree

States if the founder has an MBA degree before founding the company. All MBA-degrees will be counted in the same way regardless of which institution they were earned from.

4.3.9 Excluded founder data

Data points that were gathered but not included in the final set were earlier management consulting experience in one of the big three management consulting firms (McKinsey, Bain or BCG) or earlier investment banking experience. These were excluded because almost no founders with these characteristics were found. The number of years the founder worked before starting the company (years of professional experience) was also excluded despite being a relevant measure. Difficulty in standardizing experience data led to this exclusion as when and where you start working and if that is relevant experience becomes subjective.

4.5 Summary statistics - founder data

Occurrence of different traits at company level		
Variable	Total	% of companies
Team gender diversity	38	11.95%
Industry - Advertising	22	6.92%
Industry - Financial services	12	3.77%
Country - Norway	44	13.84%
Country - Denmark	68	21.38%
Country - Finland	88	27.67%
Country - Sweden	118	37.10692%
Industry - Machine learning	44	13.83648%
Industry - E-commerce	55	17.29560%
Industry - Healthcare	16	5.03145%

Table 1: Lists the occurence of different company characteristics

Occurence of different traits at founder level		
Variable	Total	% of founders
Number of founders	675	100%
MBA	25	3.7%
PhD	54	8.0%
Software experience	200	29.6%
Company leadership	259	38.4%
Technical degree	265	39.3%
Business degree	213	31.6%

Table 2: Lists the occurence of different founder characteristics

5. Method

5.1 Background

In order to assess which factors that impact the amount of equity funding a startup attracts two OLS-regression models with the same independent predictor variables based on team characteristics were built. One model used logarithmized total funding as the outcome variable and one model used logarithmized funding in the ventures first funding round (first funding). Control variables were also included in order to control for industry, country and age of the companies. A linear OLS-regression model is the best choice in this case since all variables are either discrete or continuous, the set contains no time series data and the aim is to assess which variables impact funding. The data on funding is also (after being logarithmized) fairly normally distributed and not heteroskedastic which makes it suitable for an OLS-regression. A full list of statistical tests regarding assumptions of linear regression can be found in appendix 1.

5.4 Variables

Since the regression model includes many variables the following table aims to provide a clear overview of variables used. Further definitions on how the data is categorized can be found in section 4.2 and 4.3.

Variable overview							
Variable name	Definition	Type	Log	Dependent	Independent	Control	Name in regression
Total equity funding (Euro)	Total equity funding received.	Continuous	Yes	Yes	No	No	lntotfund
Total first funding (Euro)	Total equity funding received in the first funding round.	Continuous	Yes	Yes	No	No	lnfirstfund
Total business degrees	Total number of founders with a business degree	Discrete	No	No	Yes	No	totbus
Total technical degrees	Total number of founders with a technical degree	Discrete	No	No	Yes	No	toteng
Total PhD degrees	Total number of founders with a PhD degree	Discrete	No	No	Yes	No	totphd
Total company leadership experience	Total number of founders with company leadership experience	Discrete	No	No	Yes	No	totc
Total MBA degrees	Total number of founders with an MBA degree	Discrete	No	No	Yes	No	totmba
Number of founders	Number of founders	Discrete	No	No	Yes	No	nroffound
Average founded companies	Average earlier founded companies	Discrete	No	No	Yes	No	avgfound

Total software experience	Total number of founders with software experience	Discrete	No	No	Yes	No	totsoft
Team gender diversity	The team consists of both male and female founders	Discrete (dummy)	No	No	Yes	No	gender
Industry - Advertising	Provides service related to advertising	Discrete (dummy)	No	No	Yes	Yes	advert
Industry - Machine Learning	Company claims to provide an AI/machine learning solution	Discrete (dummy)	No	No	Yes	Yes	aimach
Industry - Healthcare	Provides service related to healthcare	Discrete (dummy)	No	No	Yes	Yes	health
Industry - E-commerce	Provides service related to E-commerce	Discrete (dummy)	No	No	Yes	Yes	ecom
Industry - Financial services	Provides service related to financial services	Discrete (dummy)	No	No	Yes	Yes	finance
Country - Sweden	Company founded in Sweden	Discrete (dummy)	No	No	Yes	Yes	swe
Country - Finland	Company founded in Finland	Discrete (dummy)	No	No	Yes	Yes	fin
Country - Norway	Company founded in Norway	Discrete (dummy)	No	No	Yes	Yes	nor
Country - Denmark	Company founded in Denmark	Discrete (dummy)	No	No	Yes	Yes	den
Company age (years)	Number of years since company was founded	Discrete	No	No	Yes	Yes	yearsinbusiness
Time until first funding (years)	Number of years between the company was founded and first equity funding	Discrete	No	No	Yes	Yes	yearsbetweenfoundingandfirstfund

Table 3: Overview of company variables. The following table provides a broad overview of variables used in the regression models.

5.3 Model definition

Our model consists of 20 independent variables of which 9 are predictor variables and 11 are control variables. The model uses discrete independent variables and continuous dependent variables. The model is log-linear and includes 317 observations.

5.4 Regression equations

The analysis includes two regression models. One with total equity funding as dependent variable and one with first equity funding as dependent variable. Independent variables are the same in both equations.

Total equity funding - Regression equation

$$lntotfund = \alpha + ß1 * totbus + ß2 * toteng + ß3 * totphd + ß4 * totc + ß5 * totmba + ß6 * nroffound + ß7 * avgfound + ß8 * totsoft + ß9 * advert + ß10 * ecom + ß11 * aimach + ß12 * healthcare + ß13 * finance + ß14 * swe + ß15 * fin + ß16 * den + ß17 * nor + ß18 * yearsinbusiness + ß19 * yearsbetweenfoundingandfirstfund + ß20 * gender + \xi$$

Equation 1: Total equity funding. The equation shows independent and the dependent variables used in the first regression model of the thesis. The dependent variable is the natural log of total equity funding received and the independent variables are founder characteristics as well as control variables regarding industry, country and company age. In the model a represents the intercept and ε the residuals. In the models run below Sweden is omitted due to collinearity with the other country variables and is hence not shown in the regression models in 6.4 and 6.5.

First equity funding - Regression equation

$$ln(ftf) = \alpha + ß1 * totbus + ß2 * toteng + ß3 * totphd + ß4 * totc + ß5 * totmba + ß6 * nroffound + ß7 * avgfound + ß8 * totsoft + ß9 * advert + ß10 * ecom + ß11 * aimach + ß12 * healtcare + ß13 * finance + ß14 * swe + ß15 * fin + ß16 * den + ß17 * nor + ß18 * yearsinbusiness + ß19 * yearsbetweenfoundingandfirstfund + ß20 * gender + \xi$$

Equation 2: First equity funding. The equation shows independent and the dependent variables used in the second regression model of the thesis. The dependent variable is the natural log of total equity funding received in the companies first funding round and the independent variables are founder characteristics as well as control variables regarding industry, country and company age. In the model a represents the intercept and ε the residuals. In the models run below Sweden is omitted due to collinearity with the other country variables and is hence not shown in the regression models in 6.4 and 6.5.

5.5 Assumptions of linear regression

In order for a linear regression model to show accurate results certain assumptions should be met. In this thesis the Gauss-Markov assumptions are used which are a common set of assumptions. In addition to these assumptions other statistical testing was also performed. Statistical tests performed show a reasonable linear relationship between predictors and dependent variables, no issues with heteroskedasticity or multicollinearity likely no issues with endogeneity and reasonable normality of residuals and dependent variables). In addition to these the sum of residuals is very close to zero and the residuals are likely independent. All statistical tests performed on the data set are summarized and interpreted in Appendix 1.

5.5.1 - Conclusions from statistical tests

Tests performed on variables used in the regressions show no large deviations from the assumptions tested. Some small deviations from the assumptions are however present. These will likely not have a big impact on the results.

6. Empirical Results

The main empirical results of the thesis are the correlations between the prediction variables regarding founding teams and equity funding outcomes and the aim is not to build a model which perfectly predicts how much funding a startup will get.

Which variables that impact equity funding the greatest will be determined both by the size of coefficients in the regression and by examining significance.

6.1 Descriptive statistics of independent variables

Table 4 shows summary statistics for the independent variables used in the OLS-regressions in 6.4 and 6.5. For the independent variables only the number of observations, mean, standard deviation and range will be displayed since the variables generally have smaller ranges and standard deviations. The mean values shown in column C regarding founder qualities should be interpreted as the average number of founders per company that have a certain trait. For info on how common a certain trait is on the founder level see table 2. The summary shows no values of skewness and kurtosis (or other parameters regarding normality) since linear regression does not assume normality for independent variables and since the data points are discrete they will not follow a normal distribution.

Descriptive Statistics of independent variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Number of founders	318	2,12264	1,11233	1	7
Average founded companies	318	0,67884	0,90214	0	7
Total business degrees	318	0,66981	0,81456	0	4
Total company leadership experience	318	0,81447	0,84445	0	4
Total technical degrees	318	0,83333	1,02056	0	7
Total software experience	318	0,62893	0,87412	0	6
Total PhD degrees	318	0,16981	0,60186	0	4
Total MBA degrees	318	0,07862	0,28102	0	2
Number of years until first funding round	318	1,85535	1,96768	0	10
Company age	318	6,16981	2,91024	1	18
Team gender diversity	318	0,11950	0,32488	0	1
Industry - Machine learning	318	0,13836	0,34583	0	1
Industry - Healthcare	318	0,05031	0,21894	0	1
Industry - E-commerce	318	0,17296	0,37881	0	1
Industry - Financial services	318	0,03774	0,19086	0	1

Industry - Advertising	318	0,06918	0,25416	0	1
Country - Sweden	318	0,37107	0,48385	0	1
Country - Sweden	318	0,27673	0,44809	0	1
Country - Denmark	318	0,21384	0,41066	0	1
Country - Norway	318	0,13836	0,34583	0	1

Table 4: Descriptive statistics of independent variables. The table displays the number of observations, mean, standard deviation and range of the dependent variables used in the regression models.

6.2 Descriptive statistics dependent variables

Table 5 and 6 show descriptive statistics of the outcome variables. The most important numbers shown in this table are the skewness and kurtosis values since these may affect the outcome of the regression. Regarding skewness the values of -0,43763 and -0,10612 show that the data is approximately symmetric and this metric will likely not affect outcomes in the regression. The kurtosis values indicate that the distribution of the data has slightly heavier tails than a normal distribution but does not differ greatly from the kurtosis of a normal distribution which has a kurtosis value of 3. One can also note that the standard deviation is slightly higher in total equity funding than in first equity funding. Other statistical tests regarding the normality of the dependent variables can be found in appendix 1.

Total equity funding - Descriptive statistics			
	Percentiles	Obs.	317
1%	9,63933		
5%	10,91139	Mean	13,69543
10%	11,77530	Std. Dev.	1,54867
25%	12,81838		
50%	13,73289	Variance	2,39838
75%	14,86759	Skewness	-0,43763
90%	15,67356	Kurtosis	3,34156
95%	16,04143		
99%	16,65518		

Table 5: Descriptive statistics of dependent variables - Total funding. The table displays the number of observations, mean, standard deviation, range, percentiles, variance, skewness and kurtosis of the independent variable total equity funding.

First equity funding round - Descriptive statistics			
	Percentiles	Obs.	317
1%	9,63927		
5%	10,24901	Mean	12,85693
10%	10,89637	Std. Dev.	1,46210
25%	11,96166		
50%	12,98310	Variance	2,13775
75%	13,79318	Skewness	-0,10612
90%	14,55483	Kurtosis	3,22201
95%	15,18891		
99%	16,06109		

Table 6: Descriptive statistics of dependent variables - First equity funding round. The table displays the number of observations, mean, standard deviation, range, percentiles, variance, skewness and kurtosis of the independent variable total equity funding in the first funding round.

6.3 Regressions - Background

The regressions are log-linear which means that an x unit increase in a dependent variable translates into an expected $e^{x\beta}$ change in the dependent variable. For smaller changes this is approximately equal to a percentage change. When interpreting the coefficients of country variables Sweden is omitted because of collinearity and therefore the coefficients of the other country variables should be interpreted in relation to Sweden.

6.4 Regression - Total equity funding

Regression 1 - Total equity funding	
Number of obs	317
F(19, 297)	6,15
Prob > F	0
R-squared	0,2824
R-squared adjusted	0,2365
Root MSE	1,3532

Total funding	Coef.	Std. Err.	t	P>|t|	[95% Confidence Interval]	
Team gender diversity	-0,54027	0,25246	-2,14000	0,03300	-1,03712	-0,04343
Industry - Advertising	-0,10428	0,31548	-0,33000	0,74100	-0,72514	0,51659
Industry - Financial services	0,10969	0,41585	0,26000	0,79200	-0,70869	0,92807
Industry - Machine learning	0,42469	0,24535	1,73000	0,08400	-0,05815	0,90753
Country - Norway	-0,49667	0,24761	-2,01000	0,04600	-0,98396	-0,00938
Country - Denmark	0,01273	0,22191	0,06000	0,95400	-0,42400	0,44945
Country - Finland	0,26604	0,19811	1,34000	0,18000	-0,12385	0,65592
Company age	0,01574	0,03386	0,46000	0,64200	-0,05090	0,08238
Industry - E-commerce	0,14496	0,21416	0,68000	0,49900	-0,27650	0,56642
Industry - Healthcare	0,12348	0,35780	0,35000	0,73000	-0,58066	0,82761
Years between founding and first funding round	0,09522	0,04913	1,94000	0,05400	-0,00145	0,19190
Total number of MBA-degrees	-0,77638	0,28332	-2,74000	0,00700	-1,33394	-0,21882

Total number of PhD degrees	0,10298	0,15214	0,68000	0,49900	-0,19643	0,40240
Total software degrees	-0,03833	0,12317	-0,31000	0,75600	-0,28073	0,20407
Total company leadership experience	0,57883	0,10193	5,68000	0	0,37823	0,77942
Total number of technical degrees	0,19487	0,11872	1,64000	0,10200	-0,03877	0,42850
Total number of business degrees	0,32144	0,11482	2,80000	0,00500	0,09548	0,54740
Average founded companies	0,25164	0,08669	2,90000	0,00400	0,08103	0,42226
Number of founders	0,04845	0,10938	0,44000	0,65800	-0,16682	0,26371
Constant	12,33319	0,28865	42,73000	0	11,76514	12,90124

Table 7: OLS-regression - Total equity funding. The table displays results from the thesis first regression model with logarithmized total equity funding as the dependent variable.

Results in table 7 show that statistically significant predictors of total funding are: total company leadership experience, total number of business degrees, average founded companies, total number of MBA degrees, team gender diversity and whether the company is founded in Norway or not. Of these, total number of business degrees, total company leadership and average founded companies correlate with higher funding while Norwegian companies, team gender diversity and total number of MBA degrees correlate with lower funding. Variables that are almost significant are Industry - Machine learning and the number of years between founding and funding. The strongest positive coefficient in the regression is total company leadership experience and the strongest negative coefficient is total number of MBA-degrees. The R-square adjusted of 0,2365 which indicates that the model can explain 23.65% of the variability in total equity funding. In this model with quite many independent variables the R-square adjusted value will be more accurate (than R-squared) since it adjusts for variables that do not improve the predictions of the model more than by chance.

6.5 Regression - Total equity funding in first funding round

Regression 2 - Total equity funding in the first funding round	
Number of obs	317
F(19, 297)	5,99
Prob > F	0
R-squared	0,2769
R-squared adjusted	0,2306
Root MSE	1,2825

Total equity funding in the first funding round	Coef.	Std. Err.	t	P>|t|	[95% Confidence Interval]	
Team gender diversity	-0,60795	0,23927	-2,54000	0,01200	-1,07883	-0,13708
Industry - Advertising	-0,25893	0,29899	-0,87000	0,38700	-0,84735	0,32948
Industry - Financial services	0,16302	0,39411	0,41000	0,67900	-0,61258	0,93862
Industry - Machine learning	0,18405	0,23252	0,79000	0,42900	-0,27355	0,64165
Country - Norway	-0,43431	0,23467	-1,85000	0,06500	-0,89613	0,02751
Country - Denmark	0,16490	0,21032	0,78000	0,43400	-0,24900	0,57879
Country - Finland	0,14608	0,18776	0,78000	0,43700	-0,22343	0,51558
Company age	-0,09196	0,03209	-2,87000	0,00400	-0,15511	-0,02880
Industry - E-commerce	-0,09277	0,20297	-0,46000	0,64800	-0,49221	0,30666
Industry - Healthcare	-0,26099	0,33909	-0,77000	0,44200	-0,92832	0,40634
Years between founding until first funding round	0,32402	0,04656	6,96000	0,00000	0,23240	0,41565
Total number of MBA-degrees	-0,54521	0,26851	-2,03000	0,04300	-1,07363	-0,01679
Total number of PhD degrees	0,09358	0,14419	0,65000	0,51700	-0,19018	0,37735
Total software experience	-0,01017	0,11673	-0,09000	0,93100	-0,23990	0,21956
Total company leadership experience	0,42866	0,09660	4,44000	0	0,23854	0,61877
Total number of technical degrees	0,11898	0,11251	1,06000	0,29100	-0,10245	0,34040

Total number of business degrees	0,24032	0,10882	2,21000	0,02800	0,02617	0,45447
Average founded companies	0,14372	0,08216	1,75000	0,08100	-0,01798	0,30541
Number of founders	-0,05523	0,10367	-0,53000	0,59500	-0,25924	0,14878
Constant	12,34002	0,27356	45,11000	0	11,80167	12,87838

Table 8: OLS-regression - Total equity funding in the first funding round. The table displays results from the thesis second regression model with logarithmized total equity funding in the first funding round as dependent variable.

Table 8 reflects how the same independent variables as in table 7 affect the amount raised in the first equity funding round. The results are overall closely related to the results of regression 1 with some differences. Once again total company leadership experience and total number of business degrees are statistically significant predictors of higher funding while total number of MBA-degrees and team gender diversity are the best estimators of lower funding. In this model however team gender diversity has a slightly higher negative coefficient than total number of MBA-degrees. In this regression the number of years from founding until funding are significant with a positive coefficient of 0,32402 while company age correlates slightly negatively and also exhibits statistical significance. These results contrast the ones seen in table 7.

Results that are almost significant include: country - Norway and average founded companies. It is also worth noting that Industry - Machine learning which was almost significant in regression 1 is far from significant in regression 2. Another difference between the results is that significant positive variables (total number of business degrees and total company leadership experience) have smaller positive coefficients than in regression 1. Regarding coefficients of negatively correlated variables, total number of MBA degrees has a smaller negative coefficient while team gender diversity has a slightly larger negative coefficient compared to regression 1. The R-squared adjusted value of 0,2306 is similar to the one seen in table 7. However, overall statistically significant control variables are stronger in this regression while statistically significant variables regarding founder qualities are weaker. This is especially the case when examining years between founding and funding which correlates considerably stronger with first funding than with total funding.

6.6 Additional results

In order to clearly assess whether team characteristics are a better predictor of total funding than of first funding regressions were also run without control variables in order to assess the difference in R-squared adjusted value (together with differences between coefficients from the main models). The results show an R-squared adjusted value of 0.2112 for the regression on total funding and an R-square adjusted of 0.0996 in the regression on first funding. The regressions can be found in appendix 2.

7. Interpretation & Implications

Linear multiple regression models built on the data collected suggests that some characteristics of the founder team correlates with the amount of equity funding an early stage startup raises from investors.

Data used in this analysis is based on early stage information and technology industry companies founded in the Nordic countries and to which extent the results can be generalized to other countries, industries and companies in different funding stages is unclear. Results may provide insight into information and technology companies residing in markets outside the Nordic countries if these markets have similar characteristics. It is however unlikely that results can be generalized to early stage startups in sectors outside the information technology industry since capital requirements differ significantly. Moreover the results of this thesis are correlations and should not be interpreted as causal.

It is also important to note that funding is impacted by many factors. Therefore only variables with strong coefficients and significance should be interpreted as having an effect on funding. Variables with a small impact (even if significant) may be due to confounders and should not be seen as robust. Confounders of course also impact variables with strong coefficients but if a variable has a strong coefficient and is significant in both regressions the likelihood of it having an impact on funding is much greater.

Both regression models have roughly the same R-square adjusted of around 0,23 suggesting that the variables included in the analysis explains approximately a fourth of the variation in funding. It is however important to note that variables regarding team characteristics overall have larger coefficients in regression 1 than in regression 2 while several control variables have larger coefficients in regression 2. Regressions run without control variables also indicate that team characteristics have a greater impact on total funding than on the first funding round. The number of years between founding of the company and closing its first funding round has a greater impact on the amount of funding in the first round than on the total funding received by a company. That waiting longer before raising capital (in the startup world usually referred to as "bootstrapping") results in higher funding is logical since the company's value often increases over time. The impact of waiting longer before raising capital had a much smaller coefficient and was non-significant in predicting total funding which (if accepting funding as a proxy for startup success) suggests that bootstrapping is not an important factor for long term success. It is important however to understand as a startup founder that statistically (according to this data) the longer you wait to raise capital the more funding can be raised in the first round.

The fact that team characteristics somewhat better explains the total amount of money raised in a startup compared to the amount raised in the first round is somewhat surprising and the opposite of our assumptions. The idea that investors in the very early stages of a company's life must place greater emphasis on the team when making investment decisions since financial data is often lacking or unreliable is according to our analysis not the case. However, roughly the same variables regarding team characteristics are the strongest in both regression models. This suggests that the same team characteristics impact both first funding and total funding but that total funding is impacted to a higher degree. One possible conclusion to draw from this is that team characteristics correlated with funding also correlates with building better/worse companies and that the effect on funding is seen more clearly the longer the company exists. If for example having a former CEO in the team was only of signalling value then the effect should logically be seen more clearly on the first funding round than on total funding which correlates stronger with how the company actually performs. If the other way around having a CEO on the team was not of signalling value but did impact the company's actual performance then the effect on funding would be seen more clearly in the longer term. Likely team characteristics provide both signalling value and impact the company's actual performance.

Judging from our data the one characteristic that correlates best with higher funding is previous company leadership experience. An investor looking to invest in a company is evaluating its potential to grow into a successful venture and people who have led companies to success before are reasonably going to have valuable skills to achieve that goal. For the same reason, having founders with previous experience of founding companies, regardless of their success, is found attractive by investors. However, according to our data company leadership is a much better predictor of higher funding than having teams that have founded many companies before. The reason these correlates with higher funding are multifaceted but likely encompases a combination of signalling effects and skills that actually result in companies with higher valuations. Another important factor is network since people with earlier leadership positions or startup experience are more likely to have connections to sources of capital.

Concerning the education background of founder team members, only business degree holders and MBA graduates had a significant relationship with company funding. A co-founder holding a business degree had a positive effect on funding for the company. This could possibly be explained by business degree holders being more prepared for fundraising or the process of building a company. On the other hand, one co-founder having an MBA led to a significantly lower funding amount despite an MBA being a sought-after education. This is most likely due to in-group differences such as startup-founding being a highly unconventional step for an MBA graduate to take and mostly low quality MBA graduates may choose the startup path. However, the strong negative coefficient in both models is a surprising result given that other metrics of business experience and education seems to correlate with higher funding.

Having members hold engineering degrees and having software development experience did not have a significant relationship with funding. In the scope of this thesis, information and technology companies, competency in these areas is of course valuable but it might be more of a requisite/hygiene factor than a competitive advantage or unique asset. For example, software companies or companies working with AI could hardly exist without these characteristics so if they are lacking in the founder team they will instead be acquired externally. Only a handful of companies had one or more members with a Ph.D. This special expertise may certainly be beneficial or even required in some research heavy industries but since the occurrence was low in our sample a significant relationship was not possible to establish. A segmented analysis might be able to examine the possible value of PhD degree holders more closely.

A minority of teams in our data set were gender diverse and founding teams with at least one male and female co-founder received less funding with a clearly statistically significant relationship. Investors seem biased against gender diverse founding teams, deeming them less likely to succeed and factor that into investment decisions. Studies show that investors are tougher on teams with female founders which leads to lower funding for gender diverse teams (Kanze et al., 2018) and that the overwhelming majority of male investors favour same-sex investments (Diversity VC, 2017).

Regarding control variables included in the analysis, most were not statistically significant. The analysis does suggest that Norwegian companies receive considerably less funding than Swedish, Danish and Finnish companies and that waiting longer before raising funds increases the amount raised in the first round. Regarding industry differences all except AI/Machine learning companies (with total funding as dependent variable) were far from significant. When looking at total funding companies providing AI/Machine learning solutions were correlated quite strongly with higher funding and the coefficient was almost significant (P= 0,08400). This is not surprising as it has arguably been the most hyped industry of the decade with a staggering amount of funding (Pitchford, 2020).

Variables controlling for time related aspects were also included in the analysis and as earlier stated the time between founding the company and receiving its first funding round did have a significant and quite strong relationship with the amount raised in the first round. In contrast to this result, company age which logically should also correlate with higher funding did not. In fact when looking at the amount of funding in the first round company age correlated slightly negatively. This is surprising but might be a result from the time scope of the data set involving most companies founded between 2010 - 2020 in which global VC investments grew considerably (Teare, 2020). The annual growth in early stage VC investments between 2010 - 2020 may result in companies founded further back in time receiving less capital in early founding rounds. Another factor that may contribute is that successful companies founded early in the time scope of the thesis may have graduated beyond series A funding and therefore been disqualified from the study.

8. Limitations

When conducting research on early stage startups gathering data is a challenge since companies by definition are not publicly traded and specific data regarding seed and VC transactions is often lacking. The best source and a source used in many similar studies is Crunchbase, an aggregation site for early stage company information. There is always a possibility that some of the data on transactions is incorrect, or not updated, for some of the companies in the set. Given the sample of 317 companies hopefully most of these errors (if occurring) is spread between companies and not a systematic error. The same is true for the website LinkedIn.com from which founder characteristics were gathered. The decision to drop data gathered on years of professional experience was an example of this where the lack of accurate data was obvious. For parameters on education and earlier positions the data gathered is likely correct to a very high degree (Caers & Castelyns, 2011).

Another obvious flaw of the study is that the transactions are not controlled for the amount of equity sold. This means that the only conclusions one can draw from this are conclusions regarding funding and valuation since different companies may choose to sell different amounts of equity. In the funding rounds included the equity sold is within the industry standard ranges but will still differ from company to company. The best parameter to track in a study like this would have been pre-money valuation which was our initial aim. However this was not possible since this information is not accessible.

The analysis is also impacted by survival bias since there is no data on team characteristics of companies that do not or were not able to raise any funding. This means that the results of the study may not reflect which characteristics are important for company survivorship in the very early stages. An example of this is software experience which did not show a significant positive relationship with funding. Even though a software developer on the founding team is not (according to our data) correlated with higher funding it might be a crucial factor for even starting the company and being able to later raise money at all.

9. Conclusion

The results of this thesis show that some characteristics of the founding team impact the amount of equity funding an early stage startup raises. Regarding founder education a business degree is correlated with higher funding while an MBA degree is correlated with a considerably lower funding amount. Engineering or science experience did not show a significant relationship with funding and may possibly be hygiene factors rather than competitive advantages, especially in research heavy segments of the market.

Professional experience in company leadership positions was the best predictor of higher funding but earlier experience of founding companies was also correlated and significant. It is logical to expect that founders with earlier experience of company leadership will be suitable for building successful companies and these may also be better connected to sources of funding.

Our results on gender diversity strengthens conclusions from earlier research showing that women still are underrepresented in the startup world and may be affected by gender based biases resulting in lower funding.

The results also show that the importance of the founding team, with regards to funding, do not fade with time as more financial data becomes available. Instead the opposite seems to be the case since founder characteristics, judging from our data, are a better predictor of total equity funding than of first equity funding. A possible explanation being that founding teams with attractive attributes build more successful companies.

9.1 Suggestions on further research

This thesis is a comparison of which founder characteristics may be important for early stage software companies in order to secure funding. To further increase understanding this area deeper research, with both a qualitative and quantitative focus, is needed.

A granular analysis of subsegments both within industries and within specific education backgrounds could further improve the understanding of which specific competences and experience that matter the most in certain industries. The data gathered for this thesis would structurally be able to analyze industry segments but the data set needs to be considerably larger in order to establish any statistical correlations. Optimally future research should also be based on pre-money valuations in order to use company value and not funding as a measure of success. Some earlier studies already use this metric but as earlier mentioned the data is not widely accessible. Optimally this kind of research should be conducted by researchers closely connected to investors.

A study with similar independent variables as in this thesis but incorporating all companies founded and also data on companies having declared bankruptcy would also be interesting to perform. This would allow researchers to alleviate survivorship bias.

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Appendix 1 - Statistical tests

1. Assumptions of linear regression

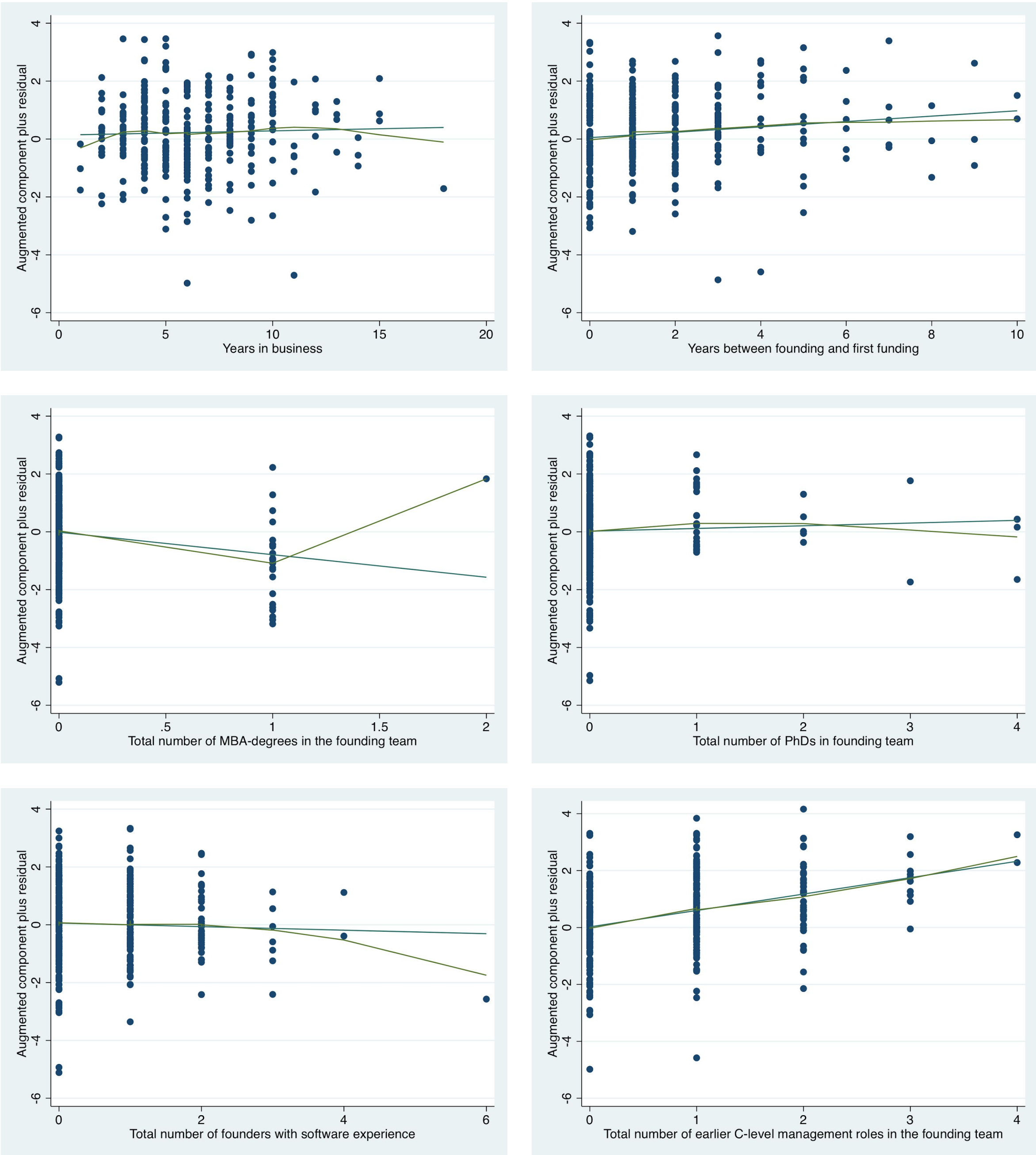
In order for a linear regression model to give the best results certain criteria should be fulfilled. Even though different sources state slightly different assumptions of linear regression a common set of assumptions used in many forms of linear regression are the Gauss-Markov assumptions which state that a regression model should be linear in parameters, that the data should be randomly sampled, that the estimators should not be perfectly correlated with each other and that the data should be exogenous and homoscedastic. If these are fulfilled the model will give the most accurate estimates sometimes referred to as Best Linear Unbiased Estimate (BLUE).

In addition to these the dependent variables should be normally distributed. It is also important (optimally) for the residuals to be normally distributed, to have constant variance (homoscedastic), have a mean of approximately zero and to be independent of each other. Below we will list the assumptions and how they are tested.

2. Linearity

In order to test if there is a linear relationship between the individual estimators and the dependent variable each non-dummy variable is plotted in an augmented-component plus residual plot (for both regressions). If the observations deviate considerably from the straight plotted line there might be non-linearity. The plots for most estimators used in our regression model show linearity. There might however be slight nonlinearity in some of the estimators (Total PhD, total technical degrees and total software experience). This nonlinearity is mostly due to a few extreme values and are likely not caused by systematic errors. However, the nonlinearity is not very strong and should likely not affect the models in a drastic way. This test is not carried out on dummy variables since these by definition have a linear relationship.

Augmented-component plus residual plots – Total funding



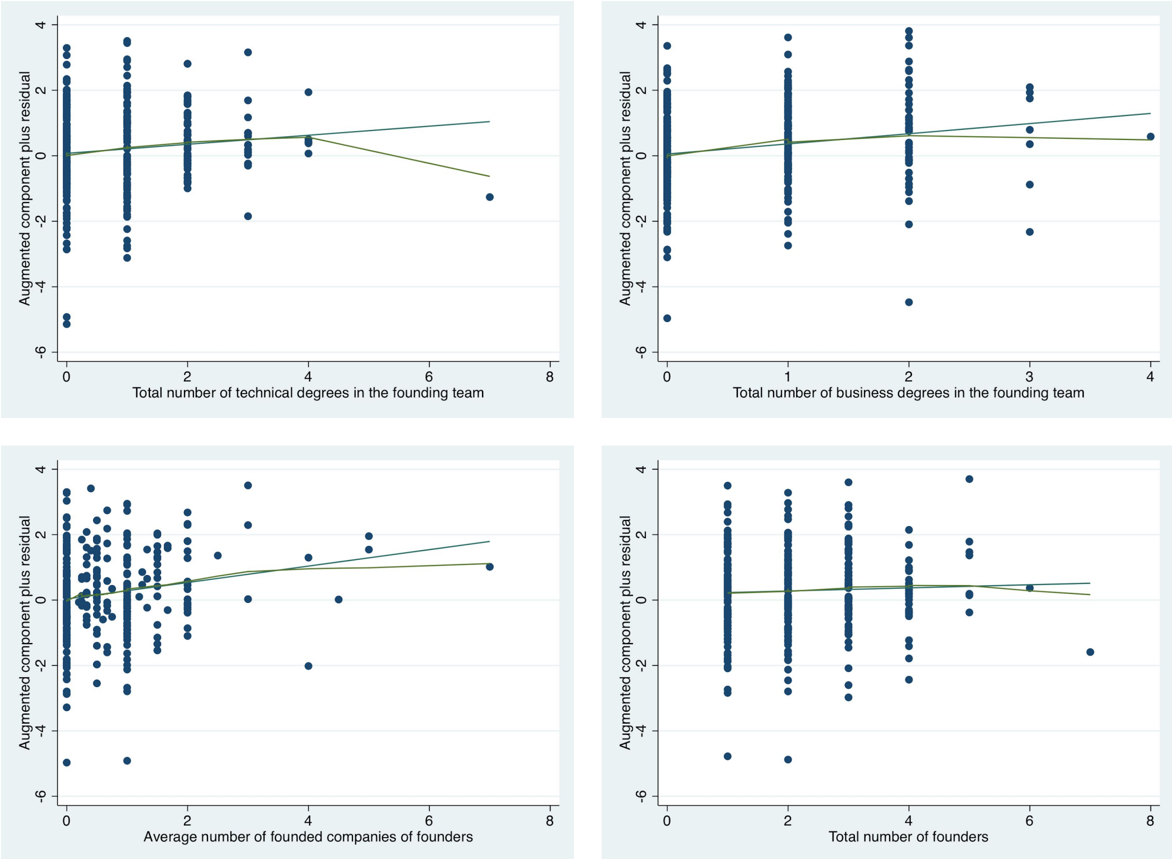
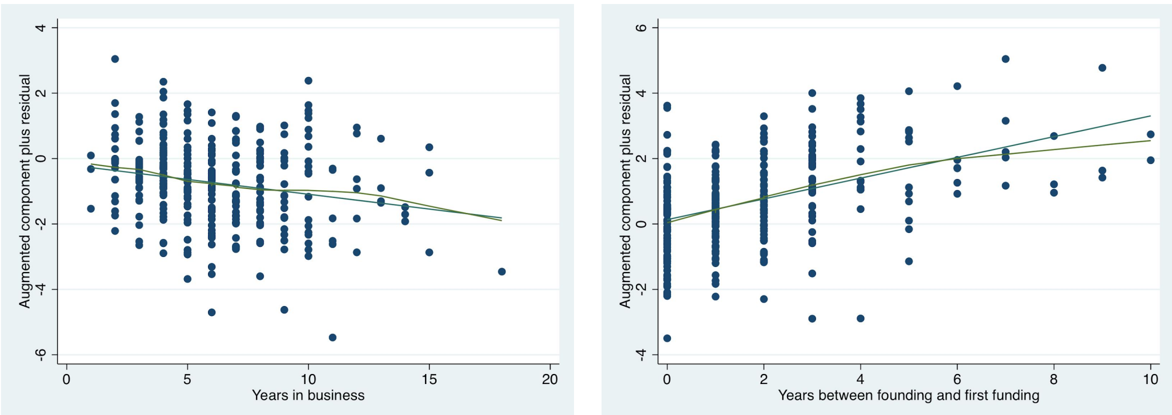


Figure 1: Augmented-component plus residual plots – Total funding

Augmented-component plus residual plots – First funding



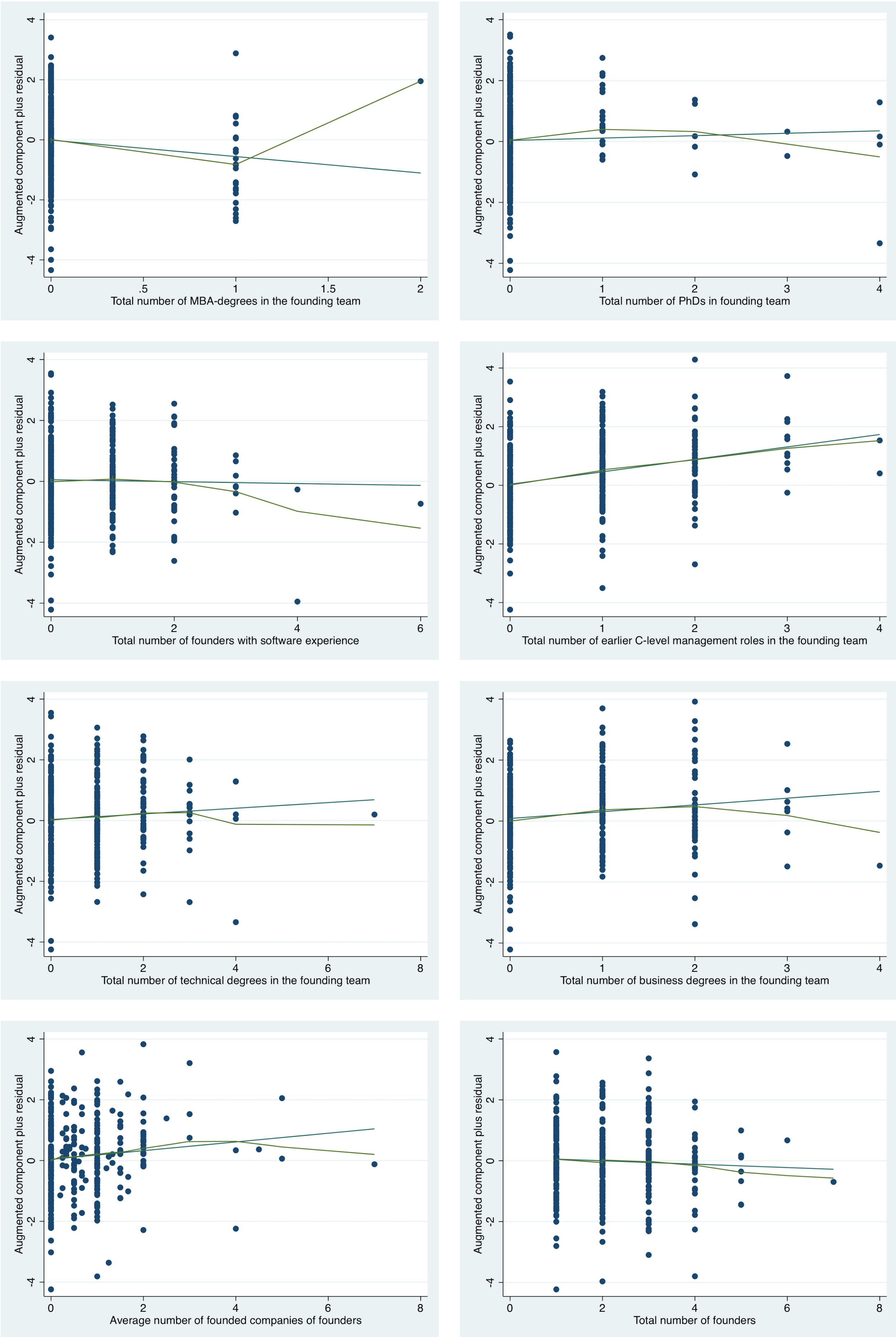


Figure 2: Augmented-component plus residual plots – First funding

3. Random sample

The data is not randomly sampled in its true sense. However, the data set in this thesis is quite narrow and the conclusions should not be used to draw inferences to a larger population which largely makes this assumption redundant. In other words, the models contain the data set it aims to explore.

4. Non-collinearity/multicollinearity

In order to assess the correlation between the estimators a VIF-test was performed. Some papers argue that a VIF < 10 is acceptable while others say 5. The values obtained from the VIF-test show no signs of problems with collinearity.

Variance inflation factors

Variable	VIF	1/VIF
nroffound	2,55	0,39147
toteng	2,54	0,39354
totsoft	2	0,49914
yearsinbus~s	1,68	0,59489
yearsbetwe~d	1,6	0,62327
totbus	1,51	0,66183
totphd	1,45	0,68910
den	1,44	0,69616
fin	1,36	0,73390
totc	1,28	0,78197
aimach	1,25	0,80282
nor	1,24	0,80359
gender	1,16	0,85902
ecom	1,14	0,87831
advert	1,11	0,89866
totmba	1,1	0,91149
finance	1,09	0,91715
healthcare	1,06	0,94153
avgfoundcomp	1,06	0,94605

Mean VIF	1,45

Table 1: Variance inflation factors

5. Exogenity

This assumption states that only the regressors should be able to affect the dependent variable and not the other way around. In other words, total funding or first funding should not affect the characteristics of the founders or any of the other independent variables. No test is carried out to assess this assumption but logically the amount of funding a company receives will not affect the education, gender and experience of the founders since the founders in almost all cases start the company before knowing anything about the amount of funding the venture will receive. The same is true for industry and country. The only variable which might be affected by endogeneity is company age (control variable) which logically may be longer if the company receives more funding.

6. Homoscedasticity

In order to test the assumption of homoscedasticity a Breusch-Pagan / Cook-Weisberg test was carried out. The test failed to reject the null hypothesis of homoscedasticity by which we can assume constant variance of the residuals.

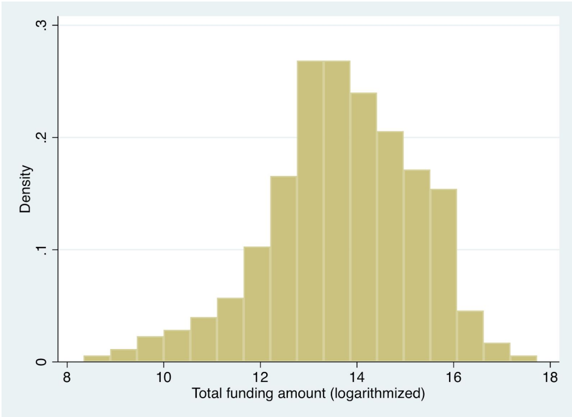
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity		
	First funding	Total funding
chi2(1)	0,46	1,55
Prob > chi2	0,4986	0,2138

Table 2: Breusch-Pagan test

7. Distribution of dependent variables

The dependent variables total equity funding and first equity funding were tested with a Skewness and Kurtosis test for normality, a Shapiro-Wilks test and plotted as histograms. The tests showed that first equity funding is very close to a normal distribution (null hypothesis of normality could not be rejected) while total funding deviated slightly from a normal distribution (null hypothesis of normality was rejected). However, the deviation from normality was small and histograms show that the distribution of the variable is quite close to a normal distribution. The skewness and kurtosis values are also in a reasonable range. This might impact the exactness of the model but should likely not be a big concern.

Histogram – Total funding and first funding



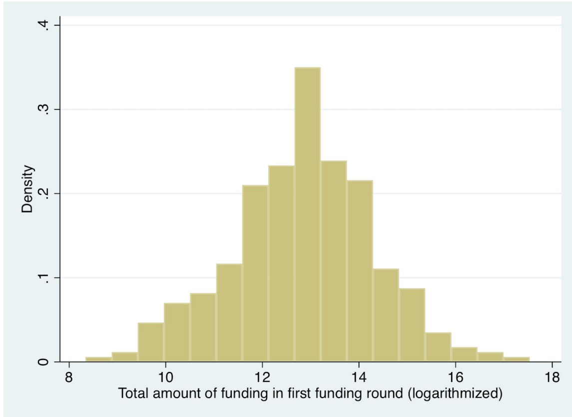


Figure 3: Distribution of total funding (ln)

Figure 4: Distribution of first funding (ln)

Shapiro-Wilks test for normal data					
Variable	Obs	W	V	z	Prob>z
Total funding	317	0.98655	3.01	2.594	0.00475
Variable	Obs	W	V	z	Prob>z
First funding	317	0.99539	1.032	0.075	0.4701

Table 3: Shapiro-Wilks test for normal data

Skewness/Kurtosis tests for Normality					
Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
Total funding	317	0.0018	0.1928	10.3	0.0058
Skewness/Kurtosis tests for Normality					
Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
First funding	317	0.4315	0.3421	1.53	0.4652

Table 4: Skewness/Kurtosis tests for Normality

8. Residuals

A linear regression model assumes:

1. Constant variance of the residuals
2. Normality of the residuals
3. Independence of the residuals
4. Zero (or close to zero) mean of the residuals

8.1 Constant variance of residuals

Constant variance of the residuals is assessed by the Breush-Pagan test earlier performed. It can also be assessed in the residuals vs fitted plots shown in 8.4.

8.2 Normality of residuals

The residuals for both regressions were plotted in a histogram, tested for normality with a Shapiro-Wilks test and plotted in a fitted vs residual plot in order to assess normality. The Shapiro-Wilks test indicates that first funding is normally distributed while total funding is not. However, just as in the case with the dependent variable total funding itself, the deviation from normality is not huge when visually inspecting the histograms.

Histogram residuals – First equity funding and Total equity funding

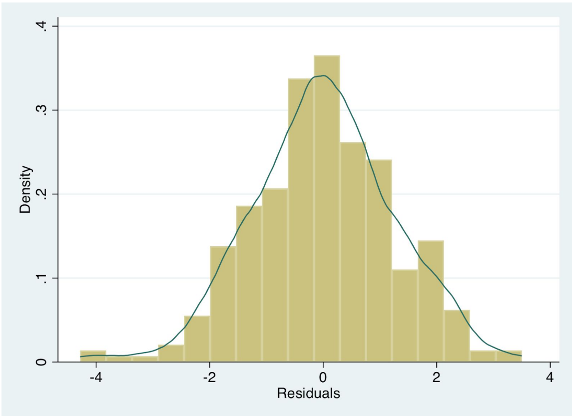


Figure 5: Distribution of residuals - first equity funding

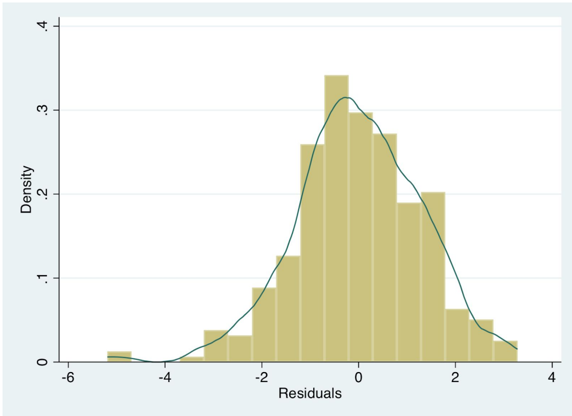


Figure 6: Distribution of residuals - first equity funding

Shapiro-Wilks test for normal data – Residuals of total funding					
Variable	Obs	W	V	z	Prob>z
residfirst	317	0.99515	1.085	0.192	0.42402

Table 5: Shapiro-Wilks test for normal data – Residuals of first funding

Shapiro-Wilks test for normal data – Residuals of total funding					
Variable	Obs	W	V	z	Prob>z
residtot	317	0.98852	2.569	2.221	0.01318

Table 6: Shapiro-Wilks test for normal data – Residuals total funding

8.3 Independence of residuals

The fitted vs residual plot showed no clear patterns (indicating independence) and were centered around zero indicating a mean of approximately zero and a constant variance (homoscedastic, which is reasonable given results from the Breusch-Pagan test). A summary of the residuals show that the mean is very close to zero for both regressions.

Residuals vs Fitted Plots

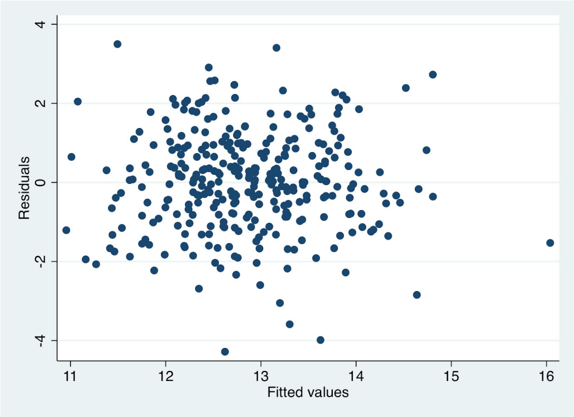


Figure 7: Residuals vs Fitted Plot – First funding

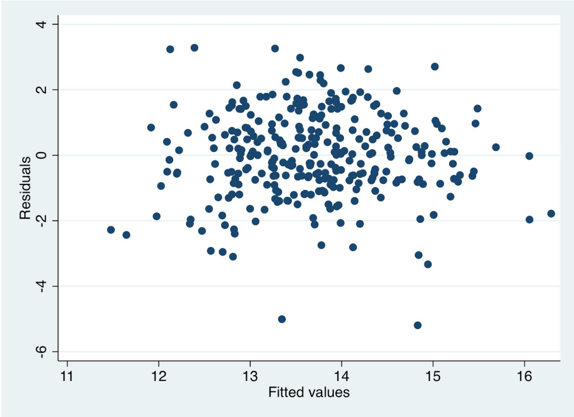


Figure 8: Residuals vs Fitted Plot – Total funding

8.4 Zero (or close to zero) mean of residuals

Summary of residuals					
Variable	Obs	Mean	Std. Dev.	Min	Max
residtot	317	1.67E-09	1.311896	-5.192386	3.283033
First funding					
Variable	Obs	Mean	Std. Dev.	Min	Max
residfirst	317	5.10E-10	1.243323	-4.282424	3.499283

Table 7: Summary of residuals

9. Summary

Tests performed on variables used in the regressions show no real issues although some small deviations from the assumptions are present. These will likely not have a large impact on the results of the regression.

Appendix 2 - Regression models without control variables

Total equity funding - No control variables	
Number of obs	317
F(9, 307)	10,4
Prob> F	0
R-squared	0,2336
R-squared Adj	0,2112
Root MSE	1,3755

Total equity funding - No control variables

Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Team gender diversity	-0,48767	0,25295	-1,93	0,055	-0,98540	0,01006
Total number of MBA-degrees	-0,75760	0,28228	-2,68	0,008	-1,31305	-0,20216
Total number of PhD-degrees	0,14152	0,15289	0,93	0,355	-0,15932	0,44236
Total software experience	-0,06037	0,12371	-0,49	0,626	-0,30379	0,18306
Total company leadership experience	0,61865	0,10175	6,08	0	0,41843	0,81887
Total number of MBA-degrees	0,26479	0,11492	2,3	0,022	0,03866	0,49091
Total number of business degrees	0,30218	0,11529	2,62	0,009	0,07532	0,52903
Average founded companies	0,23837	0,08656	2,75	0,006	0,06805	0,40870
Number of founders	0,03392	0,10927	0,31	0,756	-0,18109	0,24893
Constant	12,66415	0,18742	67,57	0	12,29537	13,03294

Table 1: OLS-regression - Total equity funding without control variables. Regression run in order to compare R-squared adjusted with the regressions from the main results.

First equity funding - No control variables	
Number of obs	317
F(9, 307)	4,88
Prob> F	0
R-squared	0,1252
R-squared Adj	0,0996
Root MSE	1,3874

First equity funding - No control variables

Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Team gender diversity	-0,54819	0,25514	-2,15	0,032	-1,05023	-0,04615
Total number of MBA-degrees	-0,60545	0,28472	-2,13	0,034	-1,16571	-0,04519
Total number of PhD-degrees	0,15314	0,15421	0,99	0,321	-0,15030	0,45659
Total software experience	-0,08724	0,12478	-0,7	0,485	-0,33277	0,15830
Total company leadership experience	0,48553	0,10263	4,73	0	0,28358	0,68749
Total number of MBA-degrees	0,19149	0,11591	1,65	0,1	-0,03659	0,41958
Total number of business degrees	0,23365	0,11629	2,01	0,045	0,00483	0,46247
Average founded companies	0,11144	0,08731	1,28	0,203	-0,06036	0,28324
Number of founders	-0,09669	0,11021	-0,88	0,381	-0,31357	0,12018
Constant	12,41588	0,18904	65,68	0	12,04390	12,78786

Table 2: OLS-regression - Total equity funding in the first funding round without control variables. Regression run in order to compare R-squared adjusted with regressions from the main results.