MASTER THESIS

# DIVERSITY IN STARTUPS

## THE IMPACT OF DIVERSITY IN THE FOUNDING TEAM ON THE SUCCESS AND FAILURE OF VENTURE-CAPITAL-BACKED COMPANIES.

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# Diversity in Startups:
# The Impact of Diversity in the Founding Team on the Success and Failure of Venture-Capital-Backed Companies.

MSc in Business Administration and E-business

*Master Thesis*


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# Abstract

Venture capital has become a dominant form of financing of European companies and thus presents a catalysator for innovation and economic growth: some of Europe's most valuable companies, such as Auto1, Klarna or Spotify, are venture-capital-backed. However, also many failed ventures are. In fact, most venture capital investments do not achieve a positive return on investment. This suggests that the decision-making process in venture capital firms is far from trivial. Especially in the early stages of a venture, data that could potentially increase the confidence in the decision-making is scarce. Consequently, investment decisions are often ill-informed and based on gut feelings. One data point, however, is present at all times: the founding team. Researchers and practitioners agree that the composition of the founding team is a valuable predictor for future success. Problematically, relevant research that is directly linked to the success and failure of venture-capital-backed companies and not to the performance of teams in general is scarce. Acknowledging this gap, in this thesis, we construct a new dataset that comprises 495 founders in 178 companies, both successful and failed. For each company, we calculate team diversity indices and subsequently compare successful and failed teams in this regard. Two statistical models confirm that increased age diversity has a positive impact on the success of a venture-capital-backed company, whereas increased gender diversity has a negative impact. Further, we found that other related variables, such as functional diversity and education diversity, do not influence success or failure. These insights show further that one, diversity is a highly complex concept that is neither good nor bad across all factors and two, diversity measures that researchers found to be influential on team performance in general do not apply in the context of venture-capital-backed companies.

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# List of Abbreviations

| | |
|---|---|
| CEO | Chief executive officer |
| CFO | Chief financial officer |
| COO | Chief operating officer |
| CSV | Comma-separated values |
| CTO | Chief technology officer |
| HR | Hazard ratio |
| IPO | Initial public offering |
| OR | Odds ratio |
| PE | Private equity |
| PhD | Doctor of philosophy (Philosophiae doctor) |
| ROI | Return on investment |
| TMT | Top-level management team |
| VC | Venture capital |
| VCF | Venture capital firm |

# 1 Introduction

Over the past decades, venture capital (VC) has become a dominant force in the financing of European companies (Pradhan, Arvin, Nair, & Bennett, 2017). In 2018, a record sum of 27.8 billion Euro has been invested in European startups, more than three times as much as in 2013 (Dealroom, 2019). Research shows that VC is a catalysator for innovation in Europe, as well as a key driver for the future growth of the European economy (Popov & Roosenboom, 2012; Pradhan et al., 2017). Not seldom, VC-backed startups have evolved to large enterprises like Klarna, Auto1 or Spotify.

But not all VC investments generate high returns for their investors – in fact, the majority of VC investments fail (Nahata, 2008; Mason & Harrison, 2002; Ruhnka, Feldman, & Dean 1992). There are a variety of reasons for this phenomenon, ranging from companies running out of money to severe conflicts among co-founders (Cantamessa, Gatteschi, Perboli, & Rosano, 2018). In order to increase the chance of a high return on investment (ROI) when selling shares of a company, a primary task of VC firms (VCFs) is to minimize the aggregated risk when confronted with an investment opportunity. This is achieved by applying a number of selection criteria (Davila, Foster, & Gupta, 2003; Dimov & De Clercq, 2006; Gorman & Sahlman, 1989).

However, the VC investment decision-making is not trivial because of the following circumstances: First, in most cases, only limited data are available that VCFs can base their investment decisions on. Particularly the absence of market and financial data leaves more room for speculations and investment decisions based on a gut feeling. Second, VCFs implement time-consuming decision-making processes to find the needle in a haystack. Considering that VCFs only invest in a small fraction of the opportunities they screen, there is potential for efficiency gains (Gompers, Gornall, Kaplan, Strebulaev, & National Bureau of Economic Research, 2016; Ng, Macbeth, & Yip, 2017). Further, research from Matusik, George, and Heeley (2008) demonstrates the presence of the similarity attraction effect in VC, indicating VCFs' bias towards favouring founding teams similar to them. How can VCFs overcome these challenges?

Research and practice agree that the quality of founding teams is one of the best predictors of the future success of a company (e.g., Goslin & Barge, 1986; Dubini, 1989; MacMillan, Zeemann, & Subbanarasimha, 1987). When evaluating founding teams, VCFs examine the personality and the experience of the individual founding team members (Hall & Hofer, 1993; Petty & Gruber, 2011), but also the diversity with regards to a founding team's education, functional experience, age, and other attributes (Eisele, Haecker, & Oesterle, 2004; Vogel, Puhan, Shehu, Kliger, & Beese, 2014; Foo, Woo, & Ong, 2005). But often, this examination only results in an educated guess. Problematically, research has not thoroughly examined the impact of diversity on venture success in the context of VC-backed companies. While VC investors favor diverse founding teams (Eisele et al., 2004; Vogel et al., 2014; Foo et al., 2005), companies such as Klarna have been successful despite being homogenous across a number of diversity attributes. Considering these shortcomings, an examination of the impact of different diversity attributes on the success and failure of VC-backed companies seems crucial for the improvement of the VC decision-making heuristics.

Surprisingly, the extant literature does not confidently answer this question. Organizational life-cycle theory suggests that founding teams' diversity attributes which drive the performance in the early stage of startups are not necessarily those desired in the later stages due to changing tasks, challenges, and opportunities associated with a venture's development stage (Boeker & Karichalil, 2002). However, most studies investigating the impact of founding team diversity have focused on distinct points in the entrepreneurial process, such as entry (Foo et al., 2005), the initial growth stages (Hmieleski & Ensley, 2007), and initial public offering (IPO) (Beckman, Burton, & O'Reilly, 2007). This limits our understanding of the importance of diversity attributes across all stages. To fill this gap, in this thesis, we collected data of ventures across all stages of the life cycle, from Seed to exit.

From a VCF's perspective, the outcome of a VC investment is binary – either it is a success, i.e., a higher return than the investment, or a failure, i.e., a lower return than the investment. However, previous research has failed to link founding team diversity to performance measures relevant in the VC context. Instead, most studies analysed a founding teams' impact on firm-level performance, such as sales and profitability (e.g. Amason, Shrader, & Tompson 2006), IPO (Beckman, Burton, & O'Reilly 2007) or growth (Eisenhardt & Schoonhoven, 1990), while other studies used, albeit less frequently, measures at the team level, such as team effectiveness (Chowdhury, 2005) and viability (Foo et al., 2005). These metrics are likely to be replaced by other performance measures emphasizing the rationale of VC investors such as funding rounds and operating status (i.e., operating or bankrupt). Examining the effects of venture team diversity on the operating status of ventures along the venture life cycle allows us to understand the overall effect of diversity on both failed and successful ventures.

In the light of inconclusive results regarding the influence of founding team diversity on venture success and failure, we applied an abductive research approach in this thesis. The purpose of the study is two-fold. First, a statistical analysis is applied to uncover correlations between diversity variables and venture team performance, examining a dataset that includes data of 178 European VC-backed companies and their 495 associated founders. Second, in a qualitative analysis we examined examploratory ventures in their success and team diversity and tested if our findings from the quantitative analysis hold true.

Our analysis agrees with the literature that diversity is not a trivial concept. We conclude that diversity cannot be interpreted as generally promoting or inhibiting success. The individual consideration of the diversity measure, such as age, gender or functional diversity is crucial as some measures have detrimental impacts on success and failure. This finding is in line with the literature on diversity. In a recent meta-analysis of 24 studies examining the relationship between team diversity and performance, the researchers could not find a consistent relationship (Webber & Donahue, 2001). Also on a more granular level, the findings of the extant literature is inconclusive as we discuss thoroughly in chapter 7.

We found that neither diversity in functional experience, diversity in the field of education nor diversity in the level of education has any significant impact on the success or failure of a VC-backed company. Furthermore, our results indicate that an increasing gender diversity has a negative impact and an increase in age diversity has a positive impact on the success of a venture.

The remainder of this thesis is organized as follows. In the next section, we present a review of the literature. We then develop a theoretical framework, which is divided into two parts. Starting with an explanation of the dynamics in VC, we investigate VC decision criteria, the VC decision-making process, and the life cycle of a venture. The second part of the theoretical framework lays the foundation for team diversity in general, as well as in the context of new ventures in particular. In chapter 4, we explain different measurements of young venture success and VCF success, describe our research design, data collection, and the methodology of our analysis. The results of the analysis follows in chapter 5 and 6. First, we apply a statistical analysis to our data set before we examine seven companies in a qualitative analysis. In chapter 7, we discuss the main findings, their implications for theory and practice, and limitations of our research before concluding this thesis in chapter 8.

# 2 Literature Review

Thus far, entrepreneurial research has primarily employed upper-echelon theory (Hambrick & Mason, 1984), to link observable demographic characteristics of venture teams to organizational outcome (Amason et al., 2006; Delmar & Shane, 2006; Eisenhardt & Schoonhoven, 1990; Chowdhury, 2005). Most previous research is based on human capital theory, examining the relationship between the presence of certain characteristics in a team and venture performance (e.g., Delmar & Shane, 2006; Streletzki & Schulte, 2013A; Baum & Silverman, 2004). However, scholars have recently begun to address the impact of a number of diversity attributes on venture performance (Amason et al., 2006; Chowdhury, 2005; Foo et al., 2005; Kaiser & Mueller, 2015).

Researchers often emphasize that diversity is distinct from human capital in that diversity informs about the variation of characteristics across team members (Hambrick, Cho, & Chen, 1996), whereas human capital only accounts for the existence of a certain capability or resource. Despite the importance of venture diversity in VC decision-making (Eisele et al., 2004; Vogel et al., 2014; Foo et al., 2005), prior research faces three methodological limitations that need to be overcome to offer clear guidance with regards to the impact of diversity on venture success and failure.

First, past research has examined the relationship between diversity and venture success only at distinct points in the venture life cycle; with ventures succeeding and failing at different points in the life cycle, an analysis of ventures across all stages becomes necessary to incorporate success criteria relevant from a VCF's perspective. Second, virtually all studies exclude failed startups from their research, limiting our understanding of the relationship between diversity and venture failure. This is an important concern as most VC investments fail (Nahata 2008; Mason & Harrison 2002; Ruhnka et al., 1992). Third, since diversity attributes and performance measures have often been aggregated to indices, it is difficult to interpret and compare findings across studies.

Research from Brixy, Sternberg, and Stüber (2012) suggests that the importance of founding team characteristics may change along the life cycle of ventures, dependent on the different challenges that founders are facing; diversity attributes influencing a venture's success at the initial stage are not necessarily those required at later stages (Boeker & Karichalil, 2002). However, most research has examined the influence of diversity on venture performance only at distinct points in the venture life cycle, limiting the understanding of the relationship between diversity and venture success and failure across the whole venture life cycle.

A substantial part of research focused on early-stage firms. For instance, Foo et al. (2005) limited their research on 51 new university spin-off ventures. Chowdhury (2004) included 79 ventures between 2 and 5 years old in his study. Similarly, a field study from Vogel et al. (2014) was limited to Seed-stage startups. While a focus on expansion stages can be found in Hmieleski & Ensley (2007), Amason et al. (2006) examined 174 "high-potential" ventures issuing IPO in their research. The only exception that we could find is research from Tzabbar and Margolis (2017) who analyzed the influence of educational diversity in founding teams on the innovativeness of biotechnology startups at different stages. However, much remains to be understood. An analysis of the prevalence of diversity attributes over the entire venture life cycle can help VCFs to understand which diversity attributes they should (not) look for when evaluating an investment opportunity.

Scholars have been examining the impact of diversity both on a firm and team performance level. Evidence on the influence of venture team diversity on team performance is mixed. While Chowdhury (2005) suggests that there is no influence of age, gender, and functional experience diversity on the effectivity and team-level cognitive comprehensiveness, Meakin and Snaith (1997) found that diverse teams tend to be more effective. Meanwhile, other scholars suggest that venture team homogeneity has a positive impact on communication and team conflict reduction (Watson, Kumar, & Michaelsen, 1993; Ancona & Caldwell, 1992) as well as on long term team performance (Steffens, Terjesen, & Davidsson, 2012). The varying results on team performance research have also been confirmed in a meta analysis by Webber and Donahue (2001). In conclusion, research on the relationship between venture team diversity and team performance presents mixed results that offer little guidance in the evaluation of venture teams.

Therefore, a review of past research, examining the relationship between venture team diversity firm performance level, may be beneficial. Scholars have analyzed several performance outcomes on firm-level such as growth, innovativeness, and VC evaluation of ventures.

Eisenhardt and Schoonhoven (1990) found that diverse industry experience and joint past experience have a positive influence on growth in young semiconductor firms. Hmielsky and Ensley (2007) examined the relationship between venture team heterogeneity (functional, educational specialty, educational level, and skill diversity) and venture performance (revenue growth and employment growth) in the context of leadership behavior (empowering and directive) and industry environmental dynamism (e.g., industry research and development intensity). Their results indicate that ventures with diverse founding teams operating in dynamic industry environments performed best when led by directive leaders, while those with homogenous venture team performed best when led by empowering leaders. However, Hmielsky and Ensley's (2007) research offers only limited generaliziable insight since diversity attributes have been aggregated to a diversity index.

Recognizing the importance of innovation in the creation of new ventures, past research has also addressed the question how venture team diversity influences the innovativeness of startups. Amason et al. (2006) differentiate between "highly novel" (initiators) and "less novel" (imitators) ventures. Their study investigates the impact of venture team diversity (age, education level, education specialization, and functional specialization) on venture performance (sales growth, market performance, and profitability) in highly novel and less novel ventures. A venture's novelty was subjectively measured by two researchers who assigned ventures into one of the following three categories, namely: "(1) offering products or services which were materially the same as products or services previously offered by other firms (2) offering products or services which represented advances in existing technologies, so-called next generation products or services or (3) offering products or services that had never before been sold and that might spawn a new industry or change the nature of an existing industry" (Amason et al., 2006, p. 133). Their results indicate a negative relationship between venture team diversity (across all diversity attributes) and performance in highly novel ventures, which was, however, not present in less novel ventures. It appears that those findings contributed to a better understanding of the relationship between diversity and firm performance, particularly because of the differentiation between novel and less novel ventures. However, the generalizability of the findings is limited as the sample included only ventures issuing an IPO.

Margolis and Tzabbar (2017) overcome this issue by considering organizational life cycle theory. In their study, the researchers examined the relationship between a venture's team educational diversity and the presence of founding experience in the context of innovation in the startup and in the growth stage of biotechnology ventures. The scholars found the impact of educational heterogeneity on breakthrough innovation to be stronger in the growth stage than in the early stage. Nonetheless, it cannot be argued that the findings are comprehensive as the focus of the study lies on biotechnology ventures and excludes other diversity attributes such as functional experience, age, and gender diversity.

Recognizing that previous research has not fully examined the link between venture team diversity and investment decision of VC providers, Foo et al. (2005) examined the influence of team diversity on judges' evaluation in a business plan competition. Their research indicates that educational diversity is positively related with the judges' evaluation while age diversity was negatively related with evaluation. These results are partly confirmed by research from Vogel et al. (2014). In a field experiment, Vogel and his associates also found that a founding team's educational and functional experience diversity have a positive and significant influence on the willingness of respondents to provide capital. However, it was also found that age and gender diversity positively impact the willingness of external capital providers to supply capital. Nonetheless, both studies offer little guidance for VC practitioners for two reasons. First, they are limited to successful seed stage startups. Second, they only reflect a VCFs decision making heuristics whereas the more important aspect is whether or not those heuristics are justified. To answer this question a team's diversity must be linked to the performance of the company from a VCF's perspective.

Concluding, inconsistencies in the selection of diversity attributes and performance measures as well as the occurrence of methodological errors, such as the aggregation of diversity attributes to indices, limit the interpretability and comparability of findings across studies (Klotz, Hmielski, Bradley, & Busenitz, 2014). Considering that most VCFs inevitably invest in failing startups, studies that only include operating ventures face a selection bias. For example, it is unclear which diversity attributes tend to be more prevalent in (failed) expansion stage startups and (failed) early stage startups. Thus, it is utterly important not only to demonstrate which diversity attributes increases success, but also which lead to failure of VC-backed startups. Finally, as ventures mature they face different opportunities and threats depending on their development stage. Previous research has not fully regarded the relationship of diversity attributes and venture success and failure depending on a venture's development stage.

Concluding the literature review, we propose the following research question: How do various diversity factors in the founding team impact the success and failure of VC-backed ventures across all stages in the venture life cycle?

# 3 Theoretical Framework

After a consideration of the extant literature and studies that are relevant to our research question, this chapter lays the theoretical foundation. We commence the theoretical framework with an explanation of the functioning of a VCF. After an introduction to this concept, we explain the selection process VCFs apply to select companies to invest in. We will show that this process is not trivial because data is scarce, especially in the early stages. To convey a better understanding of the venture life cycle, we follow up with a description of it. In the second part of the theoretical framework we thoroughly examine the concept of diversity. Starting with a broad categorization, we will narrow this concept down to specific diversity attributes of interest and finally the particularities of a venture team in contrast to other teams.

## 3.1 Venture Capital

### 3.1.1 Introduction to Venture Capital

As a type of private equity (PE), VC is a form of financing that is provided for the primary purpose of capital gain by VCFs to young, privately held companies in exchange for equity. Companies financed by VCFs have profoundly contributed to economic growth and been a prime driver for private sector employment in Europe (Pradhan et al., 2017). VC-funded firms have also impacted non-fiscal support systems, helping companies to achieve the following: developing entrepreneurial leadership skills (Keuschnigg, 2004), increasing the significance of innovations (Bottazzi & Rin, 2002; Kortum & Lerner, 2000), and amplifying the size of entrepreneurial ecosystems (Schertler & Tykvová, 2011).

Investors in VCFs are called Limited Partners. These investors are typically institutions managing large pools of capital, such as pension funds, financial firms, family offices, and governmental institutions (Gompers & Lerner, 1999; Smith & Smith, 2004). Applying modern portfolio theory, these entities typically invest a small share of their capital to VCFs based on its past returns and because of its anti-correlation with other asset classes (Cressy, 2008).

The capital acquired from Limited Partners is invested by the managers of VCFs, so-called General Partners. The goal of the General Partners is to maximize the return on investment of the Limited Partners by maximizing the number of successful investments in startups. The performance of VCFs is measured by the ROI (Cressy, 2008). VCFs generate returns in the event of an "exit", that is, when shares are being sold in an IPO or when the company is acquired by another company, also known as a *trade sale* (Cumming & Macinstosh, 2003). Alternatively, an exit may occur through selling shares on the secondary market to other investors.

However, only a small fraction of companies VCFs invest in are achieving an exit. The majority of investments result in negative returns (Cochrane, 2005; Mason & Harrison, 2002; Nahata 2008; Ruhnka et al, 1992).

To yield a return that reflects the high risk a Limited Partner is taking when investing in VCFs, VCFs need to compensate the write-offs with so-called *VC home runs* (Dimov & Shepherd, 2005). VC home runs, also known as high-flyer exits, represent the small fraction of portfolio companies that return the initial investment by a multiple greater than 10 (Cochrane, 2005; Nahata, 2008).

To identify potential VC home runs, VCFs apply different approaches to evaluate companies (Petty & Gruber 2011; Streletzki & Schulte 2013B; Zacharakis & Meyer, 2000). Monitoring the market for possible investments is therefore a key challenge VCFs are confronted with (Davila et al., 2003; Hellmann & Puri, 2002; Gorman & Sahlman, 1989).

### 3.1.2 Venture Capital Selection Criteria

Previous research has thoroughly examined the drivers in the decision making process of VCFs (Petty & Gruber, 2009; Hall & Hofer, 1993; MacMillan, Siegel, & Subba Narasimha, 1985). While the consideration of decision criteria vary from one VCF to another, four categories have been identified by previous research: product, market, financial criteria, and venture team. Following, we will briefly recapitulate research on the first three categories, before examining selection criteria in terms of the venture team more in-depth.

Characteristics of the product the company offers play an influential role in the VC decision-making process. VCFs value products providing a clear customer utility and high differentiation from other products (Eisele et al., 2004; Hall & Hofer, 1993). Furthermore, a product's defensibility, characterized by its uniqueness compared to other products and difficulty to imitate, present criteria that VCFs often regard when faced with investment opportunities (Zacharakis & Meyer, 2000; Petty & Gruber, 2011).

Regarding a venture's target market, previous research indicates that VCFs prefer investing in opportunities of large market sizes and high market growth, as these characteristics feature revenue growth and higher revenues even when only a small share of the market is gained (Zacharakis & Meyer, 2000; Hall & Hofer 1993). Furthermore, VCFs aim to reduce investment risk by avoiding investments in companies that face regulatory and political uncertainty (Kaplan & Strömberg, 2002).

In terms of a startup's financial potential, previous research found that VCFs emphasize an expected high ROI (Gompers & Lerner, 1999). This criteria is often informed by both historic data and forecasts on a venture's revenue, profitability, and other metrics indicating the monetization potential of the startups' assets (Zacharakis & Meyer, 2000; Hall & Hofer 1993).

Previous research has highlighted the importance of team criteria in a VCF's decision making process multiple times: venture team characteristics are believed to have the highest impact on a venture's success (Knockaert & Vanacker, 2013; MacMillan et al., 1985; Zacharakis & Meyer, 2000). When examining a venture team, one can differentiate between three sub-categories: The personality of the venture team, the experience of the venture team and the team's diversity (Petty & Gruber, 2009; Hall & Hofer, 1993; MacMillan et al., 1985).

In terms of a venture team's personality, previous research shows that VCFs apply selection criteria such as a venture's team ability to present its business concept in a convincing way, and its ability to perform and persevere, and to motivate employees (Eisele et al., 2004).

Research outlines that VCFs apply selection criteria with regard to the previous experience of venture teams. Positive signals in this context are, for example, familiarity with the industry, as well as previous experience in research and development (Goslin & Barge, 1986; Dixon, 1991; Beckmann et al., 2007). Subsumed under founding team experience are criteria concerning the educational background, industry experience, and functional experience. In terms of educational background, VCFs examine both the degree (i.e., level of education) as well as the field of education of founding teams (Franke, Gruber, Harhoff, & Henkel, 2008). While previous research found that technical education (Shrader, Steier, McDougall, and Oviatt, 1997) and educational capability (Shepherd, 1999) rank amongst the most important evaluation criteria overall, these results were not confirmed by other researchers (e.g., MacMillan et al.,1985; Dixon, 1991). Further, VCFs value the presence of industry experience in venture teams (MacMillan et al., 1985; Shrader et al., 1997). Industry experience is most commonly defined as a founding team's high familiarity with the target market. Across previous research, there is consensus that industry experience within the founding team is a dominant selection criterion in the VC decision-making process (MacMillan et al., 1985; Muzyka, Birley, & Lelux, 1996; Eisele et al., 2004; Franke et al., 2008).

Next to founding team's industry experience and educational background, VCFs also evaluate the founder's functional experience (Goslin & Barge, 1986; Dixon, 1991; Streletzki & Schulte, 2013B). Functional experience refers to the practical work experience of the founding team members by considering the previously held functions at other firms. While some studies found that VCFs value functional experience in marketing in particular (Goslin & Barge, 1986; Dixon, 1991), other research concludes that VCFs highly rank functional experience in management (Tyebjee & Bruno, 1981).

Finally, VCFs also examine the degree of heterogeneity with respect to different aspects in their decision-making process (Foo et al., 2005; Eisele et al., 2004; Vogel et al., 2014; Franke et al. 2008). Research from Goslin and Barge (1986) suggests that VCFs rank complementary skills in team third after functional experience in management and marketing. Dixon (1991) demonstrates in his study that VCFs prefer educational diversity over teams where all members have a similar educational background. Likewise Franke et al. (2008) found that VCFs prefer heterogeneous teams in terms of the field of education – a management-only team is, like a technical-only team, not preferred. With regards to the level of educational background, Franke et al. (2008) found an academic background to be essential, but not required from all team members, indicating that diversity is preferred here, too. Foo et al. (2005) suggests educational diversity is positively related with the judges' evaluation while age diversity was negatively related with evaluation. Furthermore, VCFs value diversity with regards to prior job experience, i.e., teams that have both worked in large firms and in startups (Franke et al., 2008).

Concluding, we find that VCFs regard a number of different selection criteria in their decision-making process. VCF's tendency to value a venture team's diversity with respect to different attributes results from the notion that the likeliness of resources being present increases with a higher venture team heterogeneity (Streletzki & Schulte, 2013A). In contrast to a purely human capital-based view, diversity allows us to evaluate founders on a team-level.

While it might be insightful to evaluate founder profiles individually in some cases, this is often accompanied by the shortcoming of not considering dynamics that result from building groups.

### 3.1.3 Venture Capital Decision-Making Process

Previous research has thoroughly examined the VC decision-making process (Petty & Gruber, 2008; Hall & Hofer, 1993; Wells, 1974; MacMillan et al., 1987) which can be divided into four phases.

In the first phase each investment proposal is screened. This initial screening is often performed by novice Venture Capitalists (Franke et al., 2008). If a deal is considered to have investment potential, VCFs proceed with the evaluation phase (Wells, 1974; Tyebjee & Bruno, 1984; Hall, 1889). The evaluation phase is most commonly subject to a meeting between an employee of the VCF and the venture's founding team. Given the hypothesized investment potential remains, the startup is further evaluated in a due diligence (Hall, 1989). In the due diligence phase VCFs attempt to collect as much information as possible about the venture's team, product, market, and financials. Findings from the due diligence process are often summarized in a synopsis (Petty & Gruber, 2008).

In successful cases, the deal structuring phase follows. The primary intention of this phase is to agree on the terms of the investment (Hall, 1989; Tyebjee, & Bruno, 1984). Given that the parties agree on the deal terms, the venture operations phase follows, in which the VCF supports the venture strategically and operationally (Wells, 1974) and monitors its activities and board meetings (Hall, 1989).

Contrary to most previous research concluding that VCFs primary criterion for positive evaluation is the quality of the management team, research from Petty and Gruber (2008) suggests that when examining the reasons for a venture's rejection VCFs pass investment opportunities primarily because of product related reasons (e.g., out of investment focus, product not compelling, no unique selling proposition).

### 3.1.4 Venture Life Cycle

Key action items, opportunities, threats, and herewith associated priorities of venture teams change over the life cycle of the company (Smith, Mitchell, & Summer, 1985). Often technology-based, VC-backed companies are particularly confronted with a changing set of problems (Kazanjian & Drazin, 1989).

This notion also finds a consideration in the VC decision-making process. VCFs do not invest a given amount of capital at once in a company, but rather take a wait-and-see approach, where they deploy reserved funds in further financing rounds if the company lives up to the expectations of the VCF (Gorman & Sahlman, 1989). Hence, the investor's expectations depend on the number of rounds raised and the expected development of the company. In practice, the number of financing rounds and the amount of capital raised differ from venture to venture. Also, both failure (i.e., bankruptcy) as well as success (i.e., exit) can occur at any time. Following, the venture life cycle from a VCF's perspective is explained in more detail, laying the foundation for success and failure definitions in chapter 5 (Eisele et al., 2004; Kazanjian & Drazin, 1989; Schmeisser, 2000; Smith et al., 1985). Previous research has established a subdivision into three stages (Kazanjian & Drazin, 1989; Schmeisser, 2000): Early Stage: idea and foundation; Expansion Stage: national and international expansion; Later Stage: restructuring and succession. Financing rounds as well as a startup's primary tasks can be assigned to these stages – an overview is provided with Figure 3-1 at the end of chapter 3.1.

#### 3.1.4.1 Early Stage

The primary focus of early stage ventures is to reach Product-Market-Fit, which can be defined as "the moment when a startup finally finds a widespread set of customers that resonate with its product" (Ries, 2011, p. 212). To reach this goal the startup's main tasks are the conceptualization of an idea to a working business model, the development of a product, and selling the product to potential customers (Block & MacMillan, 1985). Since, at this stage, a startup's resources tend to be limited, team members overlap in their functions (Sirmon, Hitt, Ireland, & Gilbert, 2011). Resulting from the need to accelerate the product development and to market the product to customers, startups often require capital from external capital providers, such as VCFs.

Commonly, the first financing round is called Pre-Seed round. The capital supplied in a Pre-Seed round is often used to carry out research and development in order to assess the viability of the venture's team idea (Fuentes & Dresdner, 2013). Other tasks may include market analysis and the development of a prototype (Tzabbar & Margolis, 2017). Second, Seed financing is supplied to companies to fund the costs of a product launch. The capital is also used to initiate the hiring process and to get further traction through marketing and sales activities (Smith & Smith, 2004). Series A financing is provided to companies to further optimize their user base and product offerings and stabilize a consistent revenue flow.

Most likely, VCFs do not invest in the Pre-Seed round (Eisele et al., 2004). Thus, the founding team must primarily draw on its own resources or those of family and friends and, if necessary, on additional public subsidies. As for the Seed and Series A round, VCF's pay particular attention to the founding team and the company's product due to the limited availability of other data (Eisele et al., 2004; Janz, 2018).

#### 3.1.4.2 Expansion Stage

When a startup enters the expansion stage, one can assume that it has reached Product-Market-Fit. This means that it has stable revenues and identified a widespread set of customers that see high utility in the product. Thus, the focus of the expansion stage lies primarily on the commercialization of the product and secondarily on the acceleration of growth through an expansion to new markets (Kazanjian & Drazin, 1989). These operations go in hand with an increased complexity of problems and the necessity to make strategic decisions about market entries and acquisitions while attaining profitability (Rubenson & Gupta, 1997; Burgelman, 1991). At the latest at this stage, ventures are also required to set up formal structures, such as functional departments (Olson & Bokor, 1995). Subsequently, startups raise a Series B round, followed by a Series C round.

Series B and Series C can be merely differentiated with regards to a startup's action items. Series B capital is primarily invested to prove that prior success can also be repeated in foreign markets (Eisele et al., 2004; Smith and Smith, 2004). The expansion in these markets often goes in hand with scaling up operational teams, such as sales, business development, and marketing. Series C financing is primarily granted to companies to invest in product innovations, the development of new markets, and to acquire other companies (Smith & Smith, 2004).

Since the team has demonstrated its skills in the previous stage and because of a higher availability of financial and market data, it can be argued that team criteria play a less important role in the VCF's decision-making process for the following investment decisions. This is further supported by the fact that, particularly starting at the Series C, more risk-averse types of investors, such as PEs come to play (Lerner, Leamon & Hardymon, 2012)

#### 3.1.4.3 Late Stage

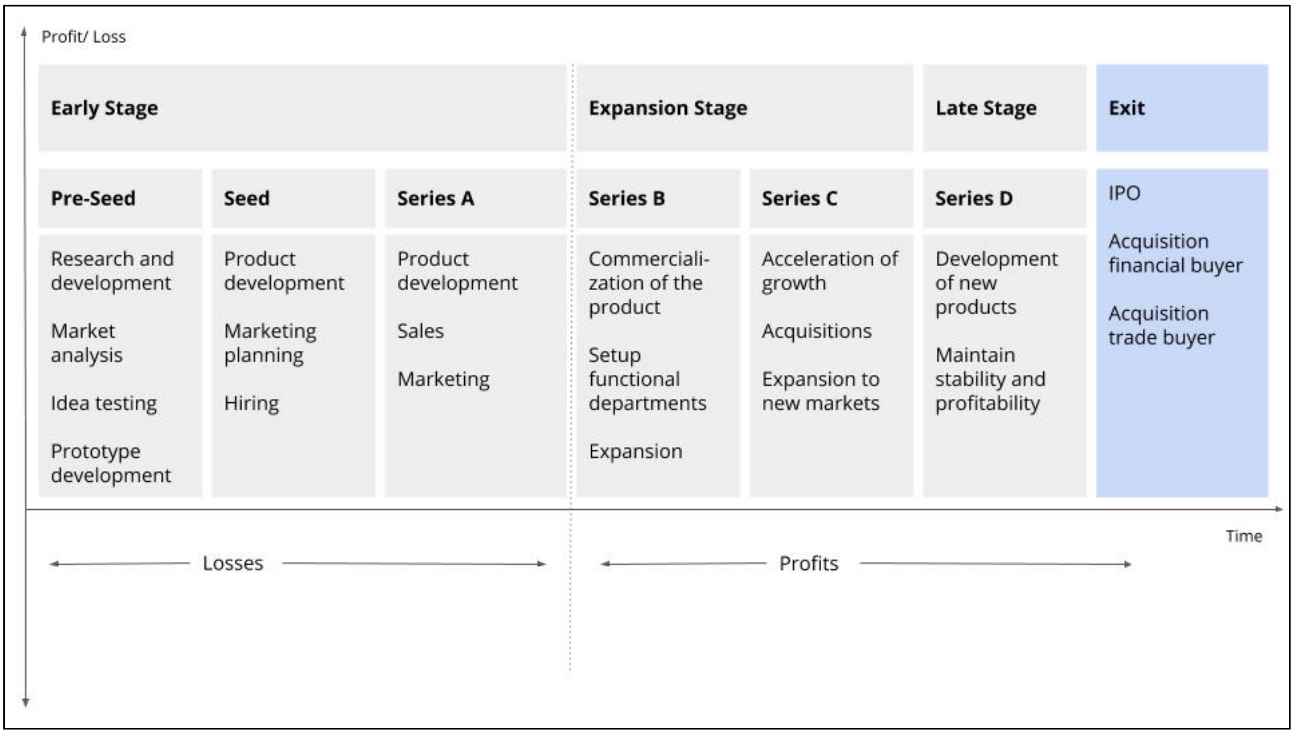
In most cases, companies end their external equity funding with the Series C and prepare for an IPO (Schmeisser, 2000). However, some companies might not be ready for an IPO because they have not reached the goals set out in their Series C, which is why they go on to Series D and even Series E. The major challenges are stabilizing the firm's position (Dodge, Fullerton & Robbins, 1994) and maintaining growth momentum and a strong market position (Tushman, 1982). These challenges are often encompassed by the introduction of a new generation of products or a further expansion into new markets (Block & MacMillan, 1985; Mann & Sager, 2007). At this stage the venture team may be partly replaced by more experienced professionals in order to set the foundation for the IPO (Gupta & Govindarajan, 1984; Dodge, Fullerton, & Robbins, 1994).

Finally, VCFs generate returns through exits. VCFs are often able to influence both timing and method of the exit and usually maintain the relevant network to path the way to an exit (Lerner et al., 2012). Exits primarily occur on three ways (Talmor & Vasvari, 2011): IPO, acquisition by a financial buyer or acquisition by a trade buyer. Traditionally, most early investors and founders sell their shares at these events.

An IPO is the process of offering corporate shares to the public. At this point a company has proper and stable financial statements, positive market sentiments, and a corporate governance in place (Lerner et al., 2012). Acquisition through trade buyers or financial buyers have yielded lower returns in the past than IPOs. Nonetheless, VCFs tend to prefer acquisitions over IPOs as means of exit as acquisitions are privately negotiated agreements that are not subject to the highly regulated processes in place for IPOs (Talmor & Vasvari, 2011). Figure 3-1 provides an overview of the key action items of ventures for each stage in the life cycle.

Figure 3-1

*Venture life cycle and investment stages adapted from Schmeisser (2000).*




In conclusion, to identify a VC home run VCFs apply a number of selection criteria when faced with an investment decision. Above all, team-related investment criteria dominate the VC decision-making. In the absence of any other data points an evaluation of the founding team is most critical in the early stage of a venture. While research shows that VCFs value diversity in teams in terms of educational background, functional experience, age and gender, little is known about the actual effect of diversity on the success factors of a VCF, investing in VC home runs.

In order to complete the picture, we will next examine the theoretical foundations of team diversity.

## 3.2 Diversity

### 3.2.1 Team Diversity

Beyond the characteristics and traits of the individual, research suggests that diversity in teams can be linked to team performance (Tsui & Gutek, 1999; van Knippenberg, De Dreu, &

Homan, 2004). Team diversity refers to the "distributional differences among members of a team with respect to a common attribute" (Bell, Villado, Lukasik, Belau, & Briggs, 2011, p. 711). Team diversity is often ascribed to have a positive impact on team performance (Ancona & Caldwell, 1992; Kochan et al., 2003; Mannix & Neale, 2005; Milliken & Martins, 1996; Pelled, 1996). Supposedly, diversity fosters greater creativity, a wider range of ideas, and thus better overall performance (Cox, 1994; Jackson, May, & Whitney, 1995). Contrary to the potential positive effects on team performance, several studies suggest that high diversity might decrease team performance, e.g., by increasing interpersonal conflict (Eisenhardt & Schoonhoven, 1990; Wagner et al., 1984).

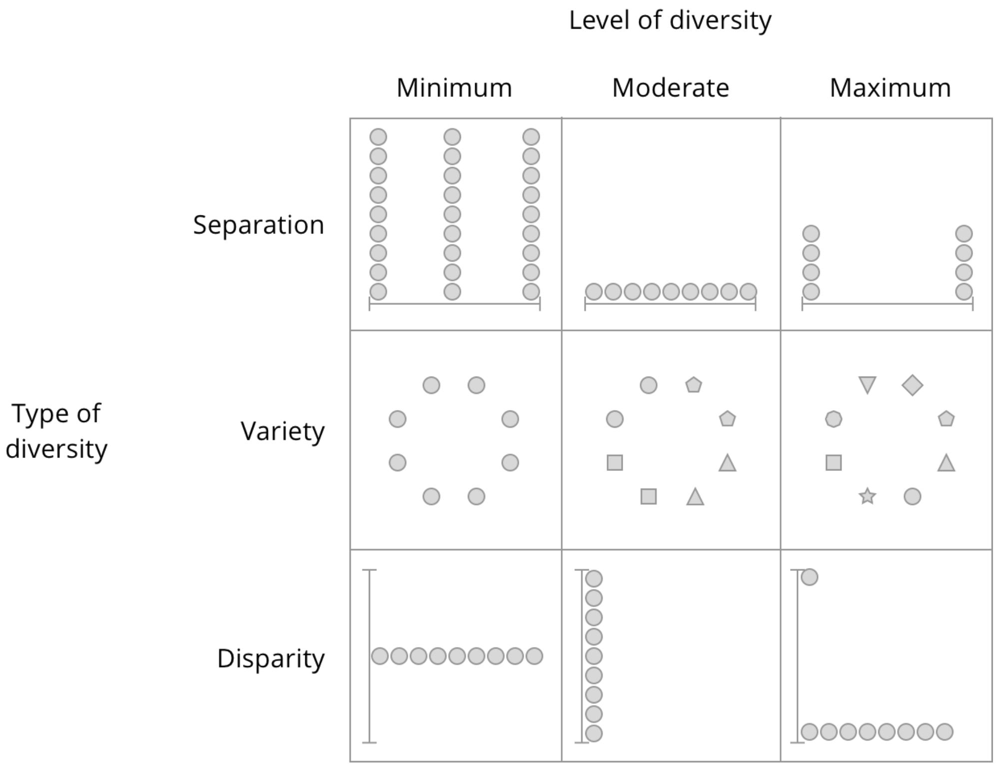
In the popular press and in the media, diversity is often considered a synonym for gender, race, and ethnic diversity. However, the research on organizational and venture teams also takes other differences into account such as age, tenure, education, and functional background (Jackson et al., 1995).

The notion that diversity enhances group performance is based on the informational diversity-cognitive resource theory (Cox & Blake, 1991; Williams & O'Reilly, 1998). This theory suggests that distributional differences can be regarded as approximations for knowledge and perspectives. Ford and Baucus (1987) suggest that individual interpretations are shaped by personal experiences and context. Partially, these experiences may be approximated by demographic traits.

Previously, diversity has been mostly acknowledged as a one-dimensional construct which led to some confusion in the research. Acknowledging the lack of definition, Harrison and Klein (2007) applied three concepts to define diversity: separation, variety, and disparity. All three concepts differ in their pattern, substance, and operationalization and consequently, their outcome.

Figure 3-2

*Types of diversity according to Harrison and Klein (2007).*




First, separation describes symmetrical differences among team members in their lateral position on a continuum, applicable for, e.g., values, attitudes, and beliefs (Harrison & Klein, 2007). In this concept, the level on the scale of interest does not matter, but only the similarity or difference between the levels (see Fig. 3-2). For example, a group exclusively composed of Bachelor's degree students would have the same (minimum) amount of separation as a group of PhD graduates (taking only the educational measure into account). Following this example, a group composed of one half Bachelor's degree students and one half PhD graduates would score the maximum amount of separation.

Variety represents categorical differences among team members in which the number of represented categories increases diversity, applicable for, e.g., functional diversity (Harrison and Klein, 2007). For example, a team consisting solely of marketing personnel would represent the minimum of diversity in terms of variety. In contrast, a group in which no two or more members share the same functionality has the highest variety.

Finally, disparity refers to differences in the concentration of desirable resources or valued assets (Harrison & Klein, 2007). Disparity describes the degree of inequality as vertical differences on a resource between the team members. In contrast to separation, disparity takes the direction of the difference between a few team members and the rest of the team into consideration. Whereas maximum separation is established when two in-groups form at opposing ends of the continuum, maximum disparity manifests when one team member is the exclusive beneficiary of a desirable resource while all others are separated from said resource on the continuum. For example, organizational tenure can be interpreted as a proxy for access to a resource within the organization: the longer the individual has been with the company, the better her access to resources. For example, a group consisting of the founder of the company and only new hires would describe the maximum of disparity.

Separation, variety, and disparity each represent a different pattern of diversity which Harrison and Klein (2007) advice applying rather than a mono-dimensional abstraction of diversity. Thus, the various types of diversity must be considered in this context. However, this framework still leaves some range for interpretation. For example, when a diversity variable is assumed to have a positive influence on team performance when its representation is increased, this variable is conceptualized as variety. In contrast, if the same variable is considered to negatively influence team performance, it can be conceptualized as disparity.

Research of diversity clusters diversity into three distinct categories, namely demographic, psychological, and informational (see Table 3-3) (Jarzabkowski & Searle, 2004; Kristinsson, Candi, & Sæmundsson, 2006).

Table 3-1

*Types of diversity, adapted from Kristinsson et al. (2016).*

| **Diversity type** | **Indicators** | **Advantage** | **Disadvantage** |
|---|---|---|---|
| Demographic | Race, gender, age | Easy to measure | Might not represent real differences |
| Psychological | Personality, behavioral preferences | Stable indicators of differences | Difficult to measure |
| Informational | Functional expertise, education, industry experience | Relatively easy to measure | Not stable indicators or differences |

First, demographic measures are indicators such as race, gender, and age. Pfeffer (1983, p. 348) states that "demography is an important causal variable that affects a number of intervening variables and processes, and through them, a number of organizational outcomes". These features are generally easy to recognize and to measure. However, they might not reflect meaningful information and might thus contribute to bias. Hambrick, Cho, and Chen (1996) suggest that demographic diversity lead to "dispersion in perspectives", or constructed realities as Finkelstein and Hambrick (1984) term it.

Second, psychological diversity refers to differences in personality and behavioral preferences. Psychological diversity is ascribed a positive influence on problem-solving capacity but also greater interpersonal conflict (Hong & Page, 2004). Psychological diversity is regarded as a robust indicator of diversity as personality is assumed to be relatively stable over time. However, psychological indicators are difficult to measure reliably and thus have not been a prominent feature of diversity in the literature (Gardner & Martinko, 1996; Pitcher & Smith, 2001).

Third, informational diversity describes differences in industry experience, education, and functional background. Teams with higher levels of informational diversity benefit from a greater pool of problem-solving perspectives, more comprehensive access to information and a higher level of creativity (Williams & O'Reilly, 1998). Therefore, informational diversity is likely to be positively correlated with increased innovative performance.

Various theories suggest to abstract the concept of diversity in teams. Most of which focus on the link between top-level management teams (TMT) and firm performance. Although distinctive from TMTs in some facets, venture teams share a meaningful resemblance to TMTs.

One of the most prominent theories regarding the impact of diversity on team performance is the upper-echelon theory (Hambrick & Mason, 1984; Finkelstein, Hambrick, & Cannella, 1996). This theory links organizational outcomes to observable demographic characteristics of top-level executives. Building on the idea of the dominant coalition (Cyert & March, 1963), the upper-echelon theory suggests that executives influence organizational performance with the decisions they make, reflecting their cognitive base (Hambrick & Mason, 1984) or executive orientation (Finkelstein et al., 1996). This takes into consideration two factors: psychological characteristics and observable traits. Fundamental to this theory is the notion that cognitive and psychological characteristics of executive orientation can be systematically linked to observable experiences, such as demographic features, e.g., age, gender, and race. Based on the idea that humans are shaped by their demographic features in their values, personalities, experiences, and other factors, these observable features work as proxy measures. For example, a 50-year-old (age) caucasian (ethnicity) man (gender) might be conceived to have more relevant experience, authority, and power than a 20-year-old Asian woman.

Taking the perceptual filters into consideration – which arguably every human applies – executives, too, are shaped by demographic features which in turn shape managerial perceptions (Hambrick & Mason, 1984) or their constructed reality (Finkelstein et al., 1996) which consequently influence strategic choices and actions.

Research on the relationship between organizational performance and group processes found that demographic diversity can influence group effectiveness in many ways and directions. Research suggests that diversity has negative effects on the frequency or quantity of communication (Smith et al., 1994; Wagner, Pfeffer, and O'Reilly, 1984), and negative effects on group cohesion (Katz, 1982; Lott & Lott, 1961; O'Reilly, Caldwell, & Barnett, 1989). More, diversity leads to more intense conflict within the group (Eisenhardt & Schoonhoven, 1990; Wagner et al., 1984), and to more prominent political activity (Pfeffer, 1981). However, diversity is also found to generate a greater variance in decision-making alternatives, and to enhance creativity and innovation (Cox, 1994; Jackson et al., 1995).

Regarding the dynamic effects of group processes, Pfeffer (1983) claims no variation in team performance beyond what is influenced by demographic traits alone. In other words, demographic measures are the critical influence on group process, more than the technique itself. In contrast, other studies (Gist, Locke, & Taylor, 1987; Smith et al., 1998), found that intervening group processes do influence team outcomes. Langfield-Smith (1992) claims that social, i.e., group, processes impact the development of shared cognitive maps, which is closely related to strategic consensus.

Previous research highlights two group processes in particular: conflict and agreement-seeking. Jehn (1995: p. 257) defines conflict as "perceptions by the parties involved that they hold discrepant views". Interpersonal conflict (also called social or affective conflict) can be defined as conflict that relates to personal and emotional relationships between people (Amason, 1996) and is said to have negative effects on group performance. Amason (1996) also found that interpersonal conflict has negative effects on both quality and acceptance of the decision. Further, Jehn (1997) found that satisfaction with the team is negatively correlated with affective conflict within the group. Similarly, research on group cohesiveness (Shaw, 1981) suggests that interpersonal conflict may reduce strategic consensus. More, Jehn (1997: p. 531), claims that "'relationship conflicts interfere with task-related effort".

In contrast, task-related conflict is found to increase group performance as it stimulates creativity and innovation as well as a variance of decision-making alternatives (Williams & O'Reilly, 1998). Minkes (1994, p. 80) describes conflict as "imperfect compatibility of views which necessarily follows from the variety of human beings". Following this notion, conflict can be understood as the tax groups have to pay to derive better outcomes.

On the other hand, agreement-seeking characteristics can be defined as behaviors that are intended to seek group consensus and agreement. Gero (1985) found that team members have more confidence in their decisions when decisions are made through agreement-seeking processes than through conflict processes. Previous research has shown that teams applying structured methods of task-oriented conflict, such as the devil's advocate or dialectic inquiry, generally produce better decisions than groups using agreement-seeking techniques. However, agreement-seeking techniques increased team members' satisfaction and acceptance of the team's decision.

Further research links diversity to comprehensiveness (Fredrickson, 1984; Fredrickson & Iaquinto, 1989; Fredrickson & Mitchell, 1984), and speed (Eisenhardt, 1989; Flood et al., 1997) in the strategic decision-making process as well as political behavior within TMT (Eisenhardt and Bourgeois, 1988). Central to the concept of group processes are the group's objective to either provide greater effectiveness (e.g., better decision-making) or greater efficiency (e.g., increasing speed or lowering costs). Table 3-4 summarizes the effects of diversity on various team factors.

Table 3-2

*The effects of diversity on various team factors.*

| Factor | Influence | Research |
|---|---|---|
| Group cohesion | Decrease (negative) | Katz, 1982; Lott & Lott, 1961; O'Reilly et al., 1989 |
| Frequency of communication | Decrease (negative) | Smith et al., 1994; Wagner, Pfeffer & O'Reilly, 1984 |
| Within-group conflict | Increase (positive/negative) | Eisenhardt & Schoonhoven, 1990; Wagner et al., 1984; Jehn 1997 |
| Political activity | Increase (negative) | Pfeffer, 1981; Eisenhardt & Bourgeois, 1988 |
| Variance in decision-making alternatives | Increase (positive) | Cox, 1993; Jackson et al., 1995 |
| Creativity and innovation | Increase (positive) | Cox, 1993; Jackson et al., 1995 |
| Speed | Decrease (negative) | Eisenhardt, 1989; Flood et al., 1997 |
| Comprehensiveness | Decrease (negative) | Fredrickson, 1984; Fredrickson & Iaquinto, 1989; Fredrickson & Mitchell, 1984 |
| Strategic consensus | Decrease (negative) | Finkelstein & Hambrick, 1996; Priem 1990; Shaw, 1981 |

The similarity-attraction theory (Byrne, 1971) suggests that homogeneous groups are more productive (i.e., efficient) than diverse teams because of a mutual attraction among the team-members with similar characteristics. This attraction might increase the frequency of communication which positively influences team performance (Wiersema & Bantel, 1992).

The theory of social categorization suggests that team members categorize other team members into subgroups which might lead to an in-group-out-group bias (Tajfel, 1969; Tajfel et al., 1979). Under some conditions (van Knippenberg et al., 2004), team members may develop an intergroup-bias (Brewer, 1979) which leads to favouritism and more cooperation with members of their in-group. Thus, the social categorization theory suggests that a team of individuals who share similar demographic traits that let them fall into the same social category should outperform a more diverse group.

The expectation model theory, which extends the social categorization theory, suggests a relationship between demographic diversity and team performance influenced by a team member's expectations of another team member's social category (McGrath, Berdahl, & Arrow, 1995). This theory suggests that the implicit assumptions one team member make about the other team member based on their demographic traits, e.g., male, caucasian, mid-40s, directly influences the expectation of their counterpart and accordingly the interaction with this person.

The previously introduced theories suggest that diversity is indeed a multi-dimensional construct. Applying the diversity framework introduced by Harrison and Klein (2007), it can be concluded that the three distinct concepts – separation, variety, and disparity – have different consequences. For one, reduced separation, i.e., greater similarity, yields positive outcomes that consequently increase team performance. Variety captures the essence of the informational diversity-cognitive resource perspective. To recap, this theory draws a positive connection between diversity and group performance as the team can leverage a broader spectrum of information and resources. These different perspectives foster debates and task-oriented conflict which lead to increased creativity and innovation. Finally, diversity in terms of disparity might increase conformity and thereby weaken creativity and innovation (Harrion & Klein, 2007). Accordingly, the concepts of separation and disparity are generally consistent with theories suggesting that diversity negatively influences team performance by decreasing cohesion and communication frequency and quality, e.g., social identity theory, similarity-attraction, and social categorization (Harrison & Klein, 2007).

Some limitations apply to the presented body of research. Regarding the upper-echelon framework (Helfat et al., 2009; Hambrick & Mason, 1984), Nielsen (2010) assesses the current research as inconclusive. Four explanations for this inconclusiveness are presented in the following. First, the concept of diversity has been extensively applied as mono-dimensional. In contrast, diversity must be interpreted as a multi-faceted construct. Not all studies underly the same definition of this concept which leads to confusion. Some simplify demographic measures as direct proxies for informational or psychological traits without clear boundaries. Second, the results of team performance are likely to be highly dependent on environmental and contextual factors, such as the organization (Finkelstein & Hambrick, 1996). Third, organizational outcomes, often assumed as the target variable, are multi-dimensional and complex. Findings with faulty abstractions of organizational objectives have led to incomparable, inconclusive, and partly contradictory results. Regarding the relationship between team diversity and innovation, researchers have suggested that inconclusive findings root from the failure to distinguish the creative ideation phase of the innovation process from the operational implementation phase (Ancona & Caldwell, 1992). Finally, and as previously mentioned, the role of team processes, which might also influence team performance, are not clear.

Although the theories underlying diversity research are intuitively appealing, meta-analytic investigations show inconclusive results. Specifically, Webber, and Donahue (2001) found no support for a demographic diversity-team performance relationship. Following up, Horwitz and Horwitz (2007) found that task-related (i.e., informational) diversity is positively associated with team performance whereas demographic diversity has no impact on team performance. Discouraged by these inconclusive findings, researchers have begun to emphasize more on mediators, moderators, and contextual factors (van Knippenberg & Schippers, 2007; Kearney & Gebert, 2009; van Knippenberg et al., 2004; Joshi & Roh, 2009). Their results show a more distinct relationship between team performance and diversity.

### 3.2.2 Specific Diversity Attributes of Interest

To conclude the previous subchapter, a team is not simply diverse; rather a team is diverse with respect to specific diversity measures (Harrison & Klein, 2007). In the following, we focus on the diversity measures most commonly studied in the literature, namely functional background, field of educational, level of education, age, and gender (Harrison & Klein, 2007). The focus on these diversity measures also has a pragmatic background as these are the features for which the most data is available, promising the most robust results. We elaborate on the selection of variables more thoroughly in chapter 4, regarding the data collection process.

Functional background diversity refers to the dispersion of work history across various functional specialization present in an organization, such as marketing, software development or finance (Bunderson, 2003). Generally, functional background, conceptualized as a variety measure of diversity, is assumed to have a positive influence on team performance. Researchers suggest that the functional background shapes a team member's perspectives and attitudes through experience and can be regarded as an important indicator of a team member's type of knowledge (Bantel & Jackson, 1989; Dearborn & Simon, 1958; Hambrick & Mason, 1984). Perspectives and attitudes are assumed to develop through experience (Fiske & Taylor, 2013) and further refined by relevant goals and rewards (Locke & Lotham; 2002). Working in a functional division of an organization exposes an employee to information and resources relevant to the functional area which the employee is influenced by. The experiences in the division should develop perspectives consistent with their functional role (Chattopadhyay, Glick, Miller, & Huber, 1999). If a greater variety of perspectives in a team enhances team performance, as assumed, a team composed of team members with different functional experience should outperform functional homogenous teams as the diverse team can draw from a broader pool of knowledge and perspectives.

Further, research suggests that diversity in knowledge and information is positively correlated with creativity (Milliken, Bartel, & Kurtzberg, 2003) and innovation (Bantel & Jackson, 1989). However, simplifying the innovation process should be well-thought-out. Researchers suggest considering the innovation process as distinct phases, broadly divided into idea generation and implementation of ideas into new products or services (West, 1990; Shane & Venkataraman, 2000). Functional diversity is assumed to especially promote the first phase in which a broader variety of perspectives enhances results whereas the implementation stage requires convergence, especially if costs or other inputs are factored into the performance measure (efficiency). Specifically, product development, design, and executive teams are likely to benefit from a greater variety of perspectives. For example, the design team benefits from a technical and business perspective in the development of new products and services (Devine, 2002) as well as in the assurance of complementarity with other organizational divisions (Ancona & Caldwell, 1992). Executive teams, such as TMTs, are challenged by a variety of ambiguous and ill-defined tasks (Devine, 2002). Expertise in relevant areas should help them make better decisions. Summarizing, functional background diversity is assumed to have a positive influence on team performance. This assumption is consistent with the concept of the informational diversity–cognitive resource perspective.

Closely related to functional experience, the field of education is found to shape skills and abilities. Ensely and Hmieleski (2005) define educational diversity as the extent to which team members have received academic experience in different fields. The exposure to different educational background enriches the team's range of perspectives and facilitates adaptability and creativity (Zimmerman, 2008).

The field of education indicates both the capabilities and the interests that an individual brings to the team. For example, a team member with an educational background in computer science can be expected to be interested in the development of a new product while those trained in business administration are usually more concerned with the commercial potential of a product (Foo et al., 2005). Since the tasks in a new venture are various, the team can benefit from a mix of educational experiences. A high level of field of education diversity is also associated with high innovation power: Parrotta et al. (2014) find a clear difference in the educational diversity between patenting and non-patenting firms with patenting firms having higher diversity on average. According to Foo et al. (2005), a high level of education predicts stronger conceptual skills in an individual whereas low levels correspond to strong practical skills. Taking the progress of a venture into consideration, a high diversity of levels in education is favourable; while practical skills are crucial in the initial stages, the growth and later-stage require more conceptual skills. Further, Hellerstedt, Aldrich, and Wiklund (2007) propose that the diversity of education level is associated with a favourable broader network across the entrepreneurial team members.

Similarly to Harrion and Klein (2007), van Knippenberg et al. (2004) argue in their categorization elaboration model that demographic diversity, e.g., gender and age, has been oversimplified in the social categorization process. They suggest the negative influence of diversity on team performance is only realized in situations where social categorization results in intergroup bias. The distinction between the mere existence of demographic features and the emergence of an intergroup-bias has been largely ignored, van Knippenberg et al. (2004) claim.

The notion that humans form first impressions and categorize another based on easily observable traits, such as age, race, and gender has long been established in the social psychology literature (Fiske & Neuberg, 1990; Messick & Mackie, 1989; Stangor, Lynch, Duan, & Glas, 1992). Observable traits convey basic information which are assumed to approximate unobservable characteristics of a person which in turn allow for a broad categorization. The application of the social category approximation is so frequently activated in daily social interaction that they became chronically accessible (Fiske & Neuberg, 1990). Attempts to manipulate the habitual categorization of sex and race to decrease social categorization based on these variables have shown little success and suggest that demographic variables are fairly consistent and robust in the short-term (Hewstone, Hantzi, & Johnston, 1991; Stangor et al., 1992).

The salience of different demographic diversity measures is, however, not equal. Harrison et al. (2002) found that surface-level measures of diversity, i.e., easily observable traits, vary in terms of a team member's perception of similarity. Race was found to have the strongest influence on a team member's evaluation of similarity. Age is suggested to have a moderate effect and gender diversity was found to have the least influence on a team member's perception of similarity. Similar results were found in MBA project teams (Zellmer-Bruhn, Maloney, Bhappu, & Salvador, 2008).

In sum, these findings suggest that diversity in age, race, and sex correlates with team performance by approximation of social categories. The negative influence of demographic diversity on team performance leads to the assumption that age, sex, and race diversity is conceptualized as a separation index. However, because sex is a categorical measure, applying the concept of diversity in terms of separation is not appropriate. Therefore, researchers often capture sex diversity in terms of variety. Although convenient, per strict definition, variety is thought only to apply when the variable a group member can assume is multi-dimensional (e.g., functional roles), and not binary (female, male).

Ireland et al. (1987) claim that individuals of similar age share similar beliefs and values, shaped by their similar experiences in life. Consistently, Pfeffer (1983) states that people of different ages have significantly different perspectives and values. Further, age is assumed to be one of the strongest predictors of a close friendship (Verbrugge, 1977) with similar age being an indicator of closer ties, longevity, and more personal depth (Fischer, 1982). Team members of a similar age are more likely than team members of different age cohorts to share common experiences and to have spontaneous conversations (Zenger & Lawrence, 1989). In a study of TMT in the banking industry, Bantel and Jackson (1989) found that age diversity is unrelated to innovation. Murray (1989) reports age diversity to positively relate to team performance. Multiple researchers found that age diversity impacts turnover positively (Tsui & O'Reilly 1989; Jackson et al. 1991; Wiersema & Bird 1995).

Gender-homogeneous groups are found to be present in a wide range of groups, such as corporate boards (Terjesen & Singh 2008), MBA student projects (Schrum & Creek 1987), and volunteer associations (McPherson & Smith-Lovin 1986). Sex is assumed to influence an individual's experiences, which in turn shapes that person's concerns, priorities, and interests (Foo et al., 2005). Such differences might decrease effective communication between male and female members of a team and lower cohesiveness. Even though conflicts are less likely to occur in homogeneous teams, mixed teams are thought to resolve emotional conflict more efficiently thanks to the complementary abilities of female and male members. Beyond complementarity, Wolley et al. (2010) found evidence that social sensitivity, needed to avoid and resolve interpersonal conflict, is positively correlated with the number of females on a team. Further, Klyver and Terjesen (2007) found that female entrepreneurs are more likely to seek and embrace information from other women.

In sum, diversity must be regarded as a "double-edged sword" (Milliken & Martins, 1996, p. 403) or a "mixed blessing" (Williams & O'Reilly, 1998, p. 120) for its opposing influence on team performance.

### 3.2.3 Venture Team Diversity

In the popular press, successful entrepreneurship is often presented as the achievement of a single outstanding individual, such as Bill Gates, Mark Zuckerberg or Steve Jobs. However, contrary to the common belief, most new ventures are founded by a team (Ruef, 2010). Although potentially presenting a better story, Apple was not founded by a single genius but by a duo: Steve Jobs and the often forgotten Steve Wozniak. Mark Zuckerberg is often presented as the eccentric genius behind Facebook but he actually started his venture with a group of people, namely Eduardo Saverin, Andrew McCollum, Dustin Moskovitz, and Chris Hughes. Next to the famous Bill Gates, Paul Allen co-founded Microsoft. The list could be extended further.

In fact, successful startups are rarely founded by one entrepreneur alone. Rather, entrepreneurs team up access a broader range of complementary skills to expand their entrepreneurial effort (Vesper, 1990). More than half of all founders work in teams of two or more (Aldrich et al., 2004; Davidsson & Honig, 2003). Especially in high-performing ventures, teams are predominant (Bird, 1989; Kamm et al., 1990; Cooper & Gimeno-Gascon, 1990; Timmons 1990).

Ruef (2002) and Ruef, Aldrich, and Cartner (2003) found that new venture teams show a bias towards homogeneity regardings age, sex, and ethnicity. Moreover, in the field of entrepreneurship, socially constructed gender stereotypes prevail with entrepreneurial traits prevailingly linked to masculine characteristics (Gupta et al., 2009).

Generally, venture teams, although sharing some important attributes with TMT, display a special type of team which faces other challenges and operate in a different environment than classic TMTs (Klotz, Hmieleski, Bradley, & Busenitz, 2014). Although the research on TMTs is well established, only little literature is available on venture team diversity, especially in the context of VC (Cooney, 2005; Harper, 2008; Soutaris & Maestro, 2010). Whereas the composition of TMTs, operating in corporations, are often appointed and situational, members of new venture teams often deliberately choose their team members. This appears to be a gap in the literature which assumes the team already exists and is well structured (Klotz et al., 2014). However, Ruef et al. (2003) show that founding teams are typically established on the basis of factors such as similarity or ecological availability rather than complementary expertise. This implies that the co-founders' expertise and perspectives often are similar. It is rare that founding teams have perfectly complementary set of skills.

New venture team members are often peers who join forces to launch a company (Reagans, Zuckerman, & McEvily, 2004). The group dynamics of this group of peers who also often are friends are often reflected on the new venture. Thus, initially no hierarchy exists and task and title allocation easily lead to affective conflicts.

Further, Sine, Mitsuhashi, and Kirsch (2006) suggest that the formalization of task positions within new venture teams is crucial for success. Concurrently, Beckmann and Burton (2008) found that the initial occupants of such task positions shape the respective position and thereby influence the long-term outcomes of the venture. Although idiosyncratic task positions such as "Chief Google Officer" can be created to better reflect the co-founder's distinct skills and tasks (Miner, 1987), startups often are inflicted to present traditional task positions such as CEO, CFO, CTO, COO, etc., to establish legitimacy and accountability demanded by the environment (Scott, 2001).

Early on, venture teams have to handle high uncertainty (Blatt, 2009) and a resource starved context (Pfeffer & Salancik, 1978) as well as unknown markets and technologies. Therefore, the founding team is advised to have a diverse functional background to address the various challenges. Simultaneously, the high uncertainty without rigid procedures in place and high stakes at the same time induces stress and might lead to interpersonal conflict. Therefore, the group must also emphasize harmony and agreeableness. The previously presented theory suggests that diverse groups tend to be less agreeable and heterogeneity fosters conflict. Therefore, the founding team faces a great challenge; to maintain diversity without sacrificing harmony. The social aspect of the founding team is critical. A recent analysis of 101 startups found that “not the right team” is the third most common reason for startups to fail and “disharmony among team” the 13th most common reason and thereby more common than “no financing” (CB Insights, 2018). Additionally, Kotha and George (2012) provide evidence that social ties within the early founding team impacts the equity holding pattern.

Juxtaposing the pros and cons of diversity, researchers found evidence that although the negative, disharmonious effects of team diversity dominates in the early stages of the team process, they are overcome relatively quickly (Pelled, Eisenhardt, & Xin, 1999). On the other side, the positive effects of diversity such as task-related conflict are more enduring. Confirming the dynamic effects of diversity, in a study of grocery store and hospital employees, Harrison, Prince and Bell (1998) report that surface level diversity, e.g., sex, age, and race, weakens over time whereas the effects of deeper-level diversity, e.g., functional or personality, strengthens over time.

# 4 Methodology

With the description of the concepts ventures, venture capital, and diversity, the previous chapter lays the theoretical foundation for the upcoming analysis. Before we continue with the quantitative analysis in the next chapter, in this chapter we describe this thesis’ methodology. We begin with an overview of the study and illustrate the procedure. Following, we describe the research design of this thesis and the data collection process we applied. This chapter closes with a discussion of credibility. In particular, we will expound the concepts reliability and validity and their role in this thesis.

## 4.1 Study Overview and Procedure

Acknowledging the unique situation in which a new venture is established, including the multi-stage innovation process, peer-based team structure, high uncertainties in markets, scarcity of resources, and predominance of male entrepreneurs, this study aims to take a more granular look on new venture diversity. We decided to establish our own definition of success and failure in the context of venture creation to approximate the target variable in the

VC decision-making process. The various success/failure definitions are explained more thoroughly in chapter 5.2.

To investigate the correlation between diversity and performance, we combined data from various sources and created a new dataset. Applying the definition of success and failure as derived in chapter 5.2, the dataset can be split into successful and failed ventures. Subsequently, with two means of statistical analysis, we examined the effects of diversity variables on the classification of success and failure in chapters 5.6 and 5.7. To draw a holistic conclusion, we challenge the findings in a subsequent qualitative analysis in chapter 6.

## 4.2 Research Design

A thorough research design constitutes the basis upon which the research question can be elaborated. The following section describes the research approach and philosophy as well as the data collection method following the approach of Saunders, Lewis, and Thornhill (2016).

Although the concepts of diversity, venture capital, and team dynamics have all been researched individually, the interplay of these concepts in the context of diversity in VC-backed ventures lacks scrutiny as we have pointed out in chapter 2. To uncover the relationship between the concepts, the main part of this thesis is exploratory. Exploratory research design is appropriate for clarifying and understanding phenomena with only little theoretical background (Saunders et al., 2016). In line with this research purpose, the forthcoming analysis features multiple statistical models in which various definitions of success and failure are tested to explore the interplay of selected diversity attributes and venture team performance.

To verify the findings from the quantitative analysis, we additionally apply a case study as a means of qualitative research. A case study allows to go into more detail and to examine features that are abstracted in the qualitative research (Bryman & Bell, 2018). However, case studies also hold the limitation that the deliberate selection of only a few cases prohibits generalization. In this study, we circumvent this issue in that we essentially use the qualitative study to corroborate the results of the quantitative study.

With the combination of qualitative and quantitative analysis, the research design of this thesis is defined by a mixed-method approach (sequential explanatory). A mixed-method research design allows to gain a richer understanding of the topic than a mono-method (quantitative or qualitative only) while offsetting the weaknesses inherent to each method by itself (Johnson & Onwuegbuzie, 2004).

Defining the research philosophy of this thesis is relevant because it influences the overall research project. Saunders et al. (2016) suggest that research philosophy reflect a continuum of beliefs, assumptions, and principles on how knowledge is generated and offers a framework of thinking that characterises how the researcher sees and interprets the context of their study. Saunders et al. (2016) suggest five predominant research philosophies in the field of business and management studies, namely, positivism, critical realism, interpretivism, postmodernism, and pragmatism. These research philosophies differ in their concept of ontology, epistemology, and axiology. The research philosophy of the thesis follows the notion of post-positivism (Saunders et al., 2016). In the following, a short consideration of the relevant concepts is presented.

Ontology is known as the theory of being and emphasizes the nature of reality (Strang, 2015). The positivistic worldview perceives reality as external. The researchers following this notion rely on theories and facts to examine and understand apparent phenomena. Therefore, results from positivistic research are able to portray the true reality (Strang, 2015). The post-positivist takes into account the complexity of the world and acknowledges that their conclusion based on limited data might not reflect the truth of nature (Ryan, 2006). Following this understanding, chapter 7 critically discusses the findings of the analysis.

Epistemology refers to the theory of knowledge. According to Strang (2015), this concept evaluates which type of knowledge is acceptable within the respective research philosophy. (Post-) Positivists are driven by facts and theoretical evidence. In that manner, chapter 3 described the theoretical groundwork while a quantitative study analysed factual data, as described in the chapter 5.

Axiology, the theory of beliefs, assesses the role of values in the research process. The positivist aims to remain neutral, value-free, and objective at all times. This means for post-positivist researchers to take on an independent, non-judging role in the data collection process. The creation of a dataset based on publicly available data, as it is done in this study, is particularly well suited for this philosophy. In contrast to more subjective means of data collection, such as in-depth interviews, publically available data from trusted sources ensures objectivity. Also, the researcher cannot interfere with the self-reported information of the respondent. Acknowledging the imperfect nature of human beings, the post-positivist considers their contribution of unintentional bias and premature assumptions to the research process. The data collection relies partly on self-reported data from the co-founders which might have stated incorrect information about themselves – deliberately or not. Which data to collect was specified based on the theoretical groundwork. However, the researchers realize that other variables might have been neglected due to pragmatic constraints of scope and time which this thesis imposes.

In the study at hand, both a deductive and an inductive approach are feasible. However, both approaches present some weaknesses. A requirement for the deductive approach is an established theory as a general rule that can be applied to a certain phenomenon to establish hypotheses and deduct a specific conclusion. As mentioned before, the research is well developed for the individual theories, such as diversity in teams, but a direct application on VC-backed venture teams is not appropriate because of the unique circumstances these ventures operate in. The weakness of the deductive approach is its strict reliance on theory-testing. Hereby, the selection of a fitting theory is not trivial and draws criticism (Bell, Brymann, & Harley, 2018). On the other side, an inductive approach allows a more explorative analysis of data upon which a theory or a framework can be developed. The inductive approach departs from a specific observation to derive a general conclusion. One criticism of the inductive approach is that no amount of empirical data alone suffices to build a thorough theory (Bell et al., 2018).

Combining the advantages of both research approaches and balancing their drawbacks, the abductive approach constitutes a third alternative. Similar to both other approaches, abduction is applied to make logical inferences and build theories. Based on a pragmatic perspective, abduction departs from a puzzling fact. In the context of this study, this fact is the inconclusive results regarding the influence of diversity on venture teams. As we described in the literature review, we found a potential flaw in the research design of previous studies that we try to overcome in this study. Following, we seek to identify reasons and conditions that clarify the phenomenon to turn the surprising fact into a matter of course (Mantere & Ketokivi, 2013). The nature of abductive reasoning involves a back-and-forth engagement with empirical data and literature (Yanow & Schwartz-Shea, 2015). In the forthcoming discussion, we try to identify the “best” explanation from competing interpretations of data.

Acknowledging the limited ability of researchers to think purely rational (as in computational reasoning), abductive reasoning highlights the importance of cognitive reasoning in theory building. Following the notion of hermeneutics (the study of interpretation), we see our research approach as a continuous dialogue between the data and our understanding, not to confirm our hypotheses but to remain open and allow for surprises.

Accordingly, the data collection in this thesis is two fold. First, the basis for the quantitative analysis is a dataset with mostly quantitative values. We use these values in a statistical analysis to uncover correlations between diversity variables and venture team performance. Other than in-depth interviews, a research technique for which a qualitative and exploratory research design is predominant, this data collection approach does not interfere with the participants' self-reported data (Saunders et al., 2016). Second, to gain a better understanding of the results from the quantitative analysis, we also apply a case study as a means of qualitative research. In this case study, we analyse exemplary ventures in their success and team diversity and test if our findings from the quantitative analysis hold true. Data we use in the description and analysis of these ventures extend the dataset with other online sources, such as news and blog articles and company websites.

Basis of the quantitative analysis is a newly created dataset in which we combine publicly available data from different sources. The data collection process is described in chapter 5.1. The data was collected as a snapshot, that is, only once for each company and founder within a period of four weeks, from July 1 to July 31, 2019. Thus, the dataset can be considered cross-sectional. Other than in a longitudinal study, time-dependent changes cannot be considered. This, however, induces drawbacks: For one, a venture that is classified as successful today might be declaring bankruptcy in the future and become unsuccessful. Therefore, the classification success/failure of a venture is not definite. Vice versa, a failed venture today would have been classified as successful some time ago. Similarly, some characteristics of founders are also time-dependent: For example, functional experience is inherently changing in the course of a founder's professional life. The experiences and skills a co-founder contributed to the venture, in the beginning, are by definition different from the experiences she or he has at the time of the data collection. Naturally, experiences accumulate over time and are most likely not be the same today, the time of measurement, as they were when the venture was founded. A longitudinal study could account for these time-dependent variables. However, given the scope of this thesis, the consideration of a longer period and continuous development is not feasible but presents a promising approach for future research.

## 4.3 Data Collection

The basis for the quantitative analysis is a newly created dataset based on publicly available data which serves as a sample. The two main sources were Crunchbase, a database of companies and founders (Crunchbase, 2019), and LinkedIn, a business and employment-oriented network website (LinkedIn, 2019). The data was sourced manually. A detailed visualization of the data processing including the data collection and preparation, data processing, and data analysis is displayed in chapter 5.2.

A sample is a finite part of a statistical population which is studied to obtain information about the whole population (Webster, 1985). For pragmatic reasons, sampling, the act of processing or selecting a suitable sample, is virtually inevitable in quantitative research (Bryman and Bell, 2011). Sampling allows reducing the population to a manageable size while maintaining statistical significance (Saunders et al., 2016). Further, sampling saves cost, makes the information process more efficient and accelerates the process of data acquisition.

Our first source, Crunchbase offers data about companies, including their founders. Crunchbase's data is updated in real-time by their community of partners, experts, data science team, and machine learning algorithms (Crunchbase, 2019). The database features information about early-stage startups to Fortune 1000 companies. The information for a company includes founding date, industry, founders, founding state, number of employees, details about founding rounds, and more.

Next, LinkedIn offers detailed information about professionals (LinkedIn, 2019). Other than Crunchbase, the data visible at LinkedIn is primarily self-reported. The data available at LinkedIn regarding an individual commonly are: name, profile picture, work experience, educational experience, and skills.

The first step in the data collection was to select companies. We aimed for the dataset to contain a balanced mix of successful and failed ventures to make meaningful distinctions between both groups. Crunchbase offers the feature to search for companies by multiple parameters, such as location, industry, number of employees, total funding amount, and operating status. We used this feature to list relevant ventures to analyze.

The sampling approach described might be prone to sampling bias and non-probability sampling. In a non-probability sample, the sampling group members are selected in a non-random manner but are deliberately selected, thus it must be assumed that not all members of the population are equally likely to be represented (Dudovskiy, 2018). Non-random selection of participants is a widespread approach in business research because sampling frames are often infeasible to define accurately. However, non-probability samples might induce severe drawbacks (Saunders et al., 2016): statistical inference might decrease reliability, rendering generalizations invalid. Although we have deliberately chosen the search parameters to obtain lists of relevant companies, we did not deliberately pick certain ventures but randomly selected from the list the search yielded. Thus, we ensured that our sample is not a non-probability sample.

At this point, we decided to limit the geographical scope of ventures to Europe. We reasoned that new ventures across Europe share a similar environment in terms of resources, such as access to finance and talents and also face similar challenges such as political systems, bureaucratic complexity, and language barriers (except the United Kingdom with English as the official language). Taking other countries into consideration such as the USA, India, or China would most probably skew the results. Thus, we set Crunchbase's search parameter *headquarters location* to *Europe*.

To ensure a reasonable balance of successful and failed ventures, we again used Crunchbase advanced search, setting the parameter *operating status* to *closed*. The results, however, did not yield an accurate list. We found this indicator to be significantly delayed compared to reality. Therefore, we also searched on Google for ventures that raised money but are not operating anymore, i.e., failed. Keywords such as "failed startups Europe" or "startup insolvent Germany" yielded websites listing relevant ventures. Combining the two services, Crunchbase and Google, we were able to create a list of ventures that are well-balanced in terms of their operating status, funding stage, and headquarters location.

The next step in the data collection was to gather the following basic information about the companies:

- Company name
- Founding year
- Headquarters location
- Operating status
- Funding in US-Dollars
- Funding status: latest series, exit

- Names of co-founders
- Number of employees

Crunchbase offers a range of useful information that we partly copied into our dataset. Although the number of employees is also estimated on Crunchbase, we approximated this measure using LinkedIn because Crunchbase only lists a wide range, e.g., 251–500. On LinkedIn, each company profile shows the number of LinkedIn members that list this company as their current employer. We are aware that this information might not be completely accurate because not all employees are LinkedIn members or do not list their current employer. However, since we abstracted this information for every company in the same manner, the number of employees still serves as a meaningful indicator. We also used the number of employees to cross-check the operating status. If a company only has a few employees on LinkedIn (< 10) but is listed on Crunchbase to be operating, we further investigated on the actual status, e.g., with a Google search. Furthermore, Crunchbase lists all funding rounds of which we copied the latest round, e.g., Series D, and, if available, the amount raised in million US-Dollars. Crunchbase also lists exits, both acquisition and IPO, partly with deal value which we took over in our dataset. All of this data was taken to create our list of companies.

Crunchbase also lists the names of the co-founders of the venture, partly with a hyperlink to LinkedIn. We cross-checked the names of the actual co-founders with blog posts and other websites, such as the official company websites. In the case of failed, i.e., funded but not operating, ventures this validation was more laborious, and arguably may be more inaccurate, as many co-founders of failed businesses tend to remove their association with their venture. If Crunchbase did not list the correct hyperlink, a Google search usually yielded the correct profile.

In the next step, the following data were abstracted from every co-founder's LinkedIn profile:

- Company association
- Year starting the venture
- Gender
- Approximate age when the business was started
- Dominant functional experience
- Dominant field of education
- Highest level of education

- Founding experience
- Startup experience
- Industry experience

Finding the company association, the year starting the venture, and the highest level of education was trivial as most founders state this information which does not allow for room of interpretation. Other information was less stable.

Starting with gender, this information was approximated by visual confirmation of the profile picture and the co-founder's name. We believe that this estimate is quite accurate, however, we were unable to verify the person's factual biological sex at birth. In this study we handle gender as the binary biological sex as assigned at birth and do not follow the notion of a non-binary gender definition.

If the age is not stated on the LinkedIn profile, abstracting the approximate age at the time of starting the venture was also not trivial. To derive a meaningful value, we applied the following heuristic: First, we defined the age when a person starts her or his university studies to be 18 years, based on current research released by the European Commission on the structure of the European education system (European Commission, 2019). Second, we took the year of starting the venture, e.g., 2016, and subtracted the year of starting university, e.g., 2008, and added 18 to yield the approximate age at the time of starting the venture, e.g. 26 (= 2016 - 2008 + 18). This, of course, cannot be accurate in all cases and presents a limitation to the data collection process. The range of age starting higher education varies and is not always 18 years. However, based on the mentioned research by the European Commission (2019) we assume 18 to be a reasonable average.

Abstracting the dominant functional experience required some interpretation from the researchers. Naturally, one's profession is not defined by a single functional experience but is the sum of her or his experience. We defined functional experience to equal the information LinkedIn members list as professional experience. Taking all professional experiences before the start of the venture into considerations, we tried to abstract a mode of all experiences with a bias for more current jobs. For example, the dominant functional experience of a founder who states CEO to be his previous position but states Head of Marketing as her role at most of her prior jobs still is considered Head of Marketing. However, if one can see a trend in positions, e.g., if this person's roles in the last three years were in management, but the prior five in marketing, the dominant functional experience is still management. In this manner, the abstracting of functional experience requires some subjectivity from the researcher. Following the post-positivist research philosophy, we try to remain neutral, value-free and objective in the data collection process. However, the abstraction of the dominant functional experience requires at least some interpretation and might impair the reliability of this study.

Similarly, the dominant field of education was extracted. However, since the change in academic subjects is not as fluid as the change in professional positions, the interpretation of this value is more stable. When in doubt, the subject of the highest level of education is considered to be dominant. For example, the dominant field of education of a founder who studied Business and Economics in her Bachelor's and then changed subject to Computer Science in her Master's is considered Computer Science.

Lastly, three binary variables (Yes/No) for founding experience, startup experience, and industry experience were considered. A person has founding experience if she has founded a company before starting the company of interest, indicated by "co-founded" or similar in her professional experience. A person has startup experience if she has had a non-junior position in a startup before. Obtaining this information is more unsafe since both the definition of a startup and the definition of non-junior position is ambiguous. Third, industry experience is given if this person has extensive knowledge in this industry. Again, this value is unstable because the industry affiliation is ambiguous. For example, a fintech (finance) startup which is based on application programming interfaces (technical) while also focusing on usability (design) has no distinct industry membership. Thus, professionals with a finance, technical or design background all have some industry knowledge. To circumvent this dilution, we only assign industry knowledge to professionals with distinct specialization which is other than the prevalent roles in startups. An example of such as specialization is a physician who worked as a medical professional before and now co-founded a medical startup. In the progression of the analysis we decided not to include these three variables in the quantitative analysis because of their high ambiguity.

Other generally relevant features to the research of diversity, such as ethnicity or cultural background could not be extracted from publically available data and were thus not included in the analysis.

## 4.4 Credibility

### 4.4.1 Research Design

To prevent the researchers from influencing the research with their subjective perspectives a good research design is paramount (Saunders et al., 2016). To ensure credibility, the researchers are encouraged to constantly revisit two important objectives of their study, namely reliability and validity.

### 4.4.2 Reliability

A high level of reliability is established by the ability of other researchers to conduct similar studies obtaining similar results that can easily be shifted to other occasions (Dubovskiy, 2018; Heale & Twycross, 2015). In other words, a reliable study is one whose findings can easily be replicated and yield consistent findings. As such, reliability assesses the consistency of all applied processes. A good indicator of reliability is the prevalence of transparency during the data analysis process (Saunders et al., 2016). To ensure reliability in this study, we thoroughly described the process of the data collection and analysis in this and the following chapters.

Although we emphasize consistency and transparency, under the present constraints of time and scope of this thesis, it was not feasible to conduct and document reliability checks such as a test-retest or follow an equivalence approach (Heale & Twycross, 2015). Still, the thoughtful derivation and reflection of measures and processes applied in the study attest reasonable confidence in the reliability of this thesis.

### 4.4.3 Validity

Validity is defined as the extent to which a theoretical concept is accurately measured (Bell, 2014; Heale & Twycross, 2015; Yin, 2017). As such, it is closely related to reliability.

The validity of a study can be established by the responsible implementation of data collection and analysis methods (Dudovskiy, 2018). Researchers must respect all factors that might influence the causal relationship of variables and possibly distort results (Saunders et al., 2016). In the following, four major types of validity relevant to this research are examined, namely construct validity, internal validity, external validity, and ecological validity.

In the research at hand, construct validity might have been impeded by the nature of the data which is in large parts self-reported. Also, in the process of abstraction of data into a usable dataset, some information may have been omitted or altered.

The level of internal validity is determined by testing if the causal relationship discovered between the independent and dependent variables are influenced by any other factors (Bell et al., 2018). In the context of this study, the dependent variable of venture success of failure is, of course, not solely dependent on diversity measures. However, statistical measures allow formulating abstract correlation. These results must not be considered as evident causal relationships but foremost as mere correlations. As previously explored, diversity features, such as age or race, often are proxies for other characteristics, such as knowledge or personal perspectives. These proxies must be considered as quick yet defective heuristics of human nature. Thus, causality can only partly be stated. We are cautious with premature conclusions regarding the causality of variables. Assumptions of causal relationships under consideration of internal validity are discussed in chapter 7.

External validity refers to the generalization of study results. Accordingly, the sampling method applied is crucial to assess the level of external validity of every study (Saunders et al., 2016). The sample used in this study might be considered as a convenience sample. Non-probability samples are prone to produce biased samples. Therefore, the potential for generalisation of the findings based on non-probability samples is limited. As we have described in chapter 4.3, we did not deliberately pick certain ventures but randomly selected these from Crunchbase after setting applicable search criteria. Thus, we can assume that our sample is not a non-probability sample.

Ecological validity examines the extent to which the study conclusions can be generalized to the context and settings in which the phenomenon is generally observed. This study's approach, which disregards people's subjective and incoherent opinions and behaviours, allows for a high ecological validity. In contrast to an experiment in which the participants are asked to imagine a certain situation, here, the event of interest – the creation of a venture – must have been an actual event in the past.

# 5 Quantitative Analysis

The previous chapters established the foundation on which the following data analysis bases. Subsequently, this chapter starts with a description of our multi-level data analysis process of which the first level is the data collection and preparation followed by the data processing and finally, the data analysis. We follow up with a description of the relevant variables, namely dependent, control, and independent variables. Following an abductive research approach that calls for an extended handling of data, we define three different variables for the definition of success and failure based on the literature review and the theoretical foundation. In the statistical models we iterate the dependent variable to yield robust results. The independent variables are the diversity indices which are calculated for each company with the information we gathered about the founders. We were able to derive five meaningful diversity measures, namely age diversity, functional experience, field of education diversity, and level of education diversity. However, it was not possible to calculate each measure for every company because of missing values. Again, to ensure robust results, we applied two different means of calculating the diversity index, namely the Shannon-Wiener and the Simpson index. The configuration of the applied diversity index and success/failure definition led to the definition of six models that are tested individually.

In the next subchapter, we proceed to present the descriptive statistics which describe basic statistics such as the average age of a co-founder, financing per stage, the distribution of educational levels, and fields of education. Following, we analyze the relationship between the various diversity measures and the success and failure of a VC-backed company with a logistic regression. We first describe our approach and test for assumptions before we present the results of all models. To ensure the robustness of the results of the logistic regression, we apply a second static analysis, namely the Cox proportional-hazards model of the category of survival analysis. Again, we first describe the background of a hazard function, test for assumptions and then present the results. We also examine applicable limitations to this model.

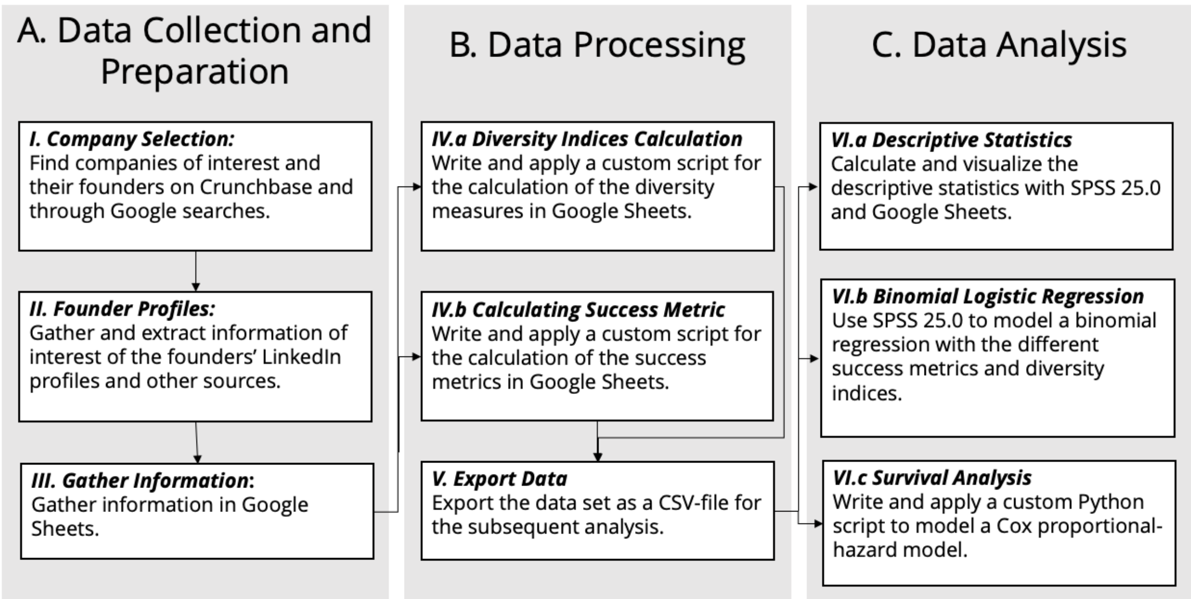
## 5.1 Analysis Process

For the analysis in this chapter we used Google Sheets (Google, 2019b), SPSS Statistics 25.0 (IBM Corp., 2017), and Google Colaboratory (Google, 2019a) with Python (Rossum & Drake, 2001) and the lifelines package (Davidson-Pilon et al., 2019).

The following data processing procedure is visualized in Fig. 5-1. In the first step, the data was gathered in Google Sheets, a web-based spreadsheet program offered by Google (Google, 2019b). Additionally to the built-in functionalities of this software, we programmed custom app scripts in JavaScript for the calculation of the diversity indices (see Appendix A) and the success description (see Appendix B). The dataset was then exported as a CSV file and imported into SPSS (IBM Corp., 2017) for the modelling of the logistic regression and into Google Colaboratory for the subsequent survival analysis. Google Colaboratory is a web research tool for data analysis and machine learning education and research (Google, 2019a). We used common Python packages such as numpy (Oliphant, 2006) and pandas (McKinney et al., 2010) for the data handling and the lifelines package (Davidson-Pilon et al., 2019) for the modelling of a Kaplan-Meier model and a Cox proportional-hazard model (see Appendix E).

Figure 5-1

*Data processing diagram.*



## 5.2 Description of Variables

### 5.2.1 Dependent Variable

The definition of success and failure is not clear-cut. Therefore, the dependent variable in the analysis reflects three different definitions of success and failure.

Most distinctive, we argue that a venture team that has achieved to sell the company for a multi-million US-Dollar amount or went public (IPO) is successful. In this scenario, the investor, e.g., the VCF, realizes their ROI and receives their share. Thus, the first definition of success (success1) defines a successful startup if is has exited, that is, by acquisition or IPO:

**IF** has exit.

Next, we extend this definition arguing that a venture that is currently operating and in a founding round greater than Series A shows some promise. At this point, we claim, the founding team has already overcome several challenges and proven themselves capable. In the following growth stage of the venture, the team grows and more data becomes available. Thus, the following investment decisions become less reliant on the founder team and more dependent on other data, such as market dynamics. Concluding, in the second definition of success (success2) we regard a venture successful if it is currently operating and at least in a venture capital financing round bigger or equal to Series B:

**IF** has exit **OR** (funding round > Series A **AND** is operating).

Last, we diverge from the assumption that the founding rounds are ideal proxies for success and reason that a successful venture is one that has raised more than or equal to 10 million US-Dollars in funding or has more or equal to 50 employees while it is currently operating. Thus, the last success definition (success3) is the following:

**IF** has exit **OR** ((raised ≥ 10 M $ US **OR** number of employees ≥ 50) **AND** is operating).

We define failure or unsuccessful ventures, in each scenario, as not operating and not having exited (successfully exited companies might not be operating anymore). Our sample only comprises ventures that have raised at least one financing round (Seed) so it can be assured that all failed ventures have some touchpoints with a VCF. Thus, our failure definition is the following:

**IF NOT** is operating **AND NOT** has exit.

Thus, the dependent variable, coded as 1 (success) and 0 (failed) is dichotomous.

### 5.2.2 Control Variables

The founding year and the number of co-founders of each venture were taken into consideration and tested for significant impact on the model as control variables. We deliberately excluded headquarters location as a control variable because the dataset shows a bias towards failed German startups. The reason for this bias lies in the data collection process, more specifically, in the selection of ventures. As we have explained in chapter 4, we found Crunchbase's search feature regarding operating status to be faulty at times. Therefore, we also used search engines to source failed ventures. Probably due to Denmark's close geographical proximity to Germany and our search history, the results the search engines yielded were largely German blogs and news outlets. Hence, we do not implement this variable as a control measure lest we introduce a bias in the analysis.

### 5.2.3 Independent Variables

The independent variables are represented by diversity indices for age, gender, functional experience, field of education, and level of education. Diversity must be calculated differently for metric and non-metric variables. Age diversity, as a metric variable is calculated as the standard deviation of the team member's ages. Gender diversity, functional diversity, field of education diversity, and level of education diversity are non-metric variables and are calculated accordingly.

Gender, or sex, is assumed to take either the value female or male, coded as F or M. One team member has exactly one gender. Merging the values results in a diversity string, which can be processed later. For example, a team of two male co-founders would be represented by MM, a team of two female and one male co-founder would be represented by FFM.

To calculate the diversity for functional experience, the founders' experience must first be grouped. From the abstracted but unstructured values for dominant functional experience for every founder, we constructed eight groups and allocated exactly one to each founder. To define the groups, we first listed the dominant functional experience of each founder and tried to find meaningful distinct categories. Of course, the boundary of each group cannot be clear-cut. For example, the role of a Chief Marketing Officer is both a management role and a marketing role. This ambiguity is especially apparent for management roles. In unclear cases, we oriented the categorization on the more distinct role, for example, in the case of the Chief Marketing Officer, marketing. Find a non-exhaustive categorization guide in Appendix C.

Thus, we defined eight groups of functional diversity:

- Marketing
- Technical
- Management
- Operations
- Finance
- Consulting
- Creative
- Other

The functional groups are abbreviated by letters A to H in the forthcoming analysis. Again, the functional experience letters can be merged into one string. For example, a team represented by BC would represent a team of two with the first co-founder having the experience B (technical) and the second co-founder having the experience C (Management).

Similar to the definition of functional experience groups, the calculation of field of education diversity also requires some an abstraction into higher-level groups. We aligned the definition of groups with the classifications made by universities, such as the Copenhagen University ("Areas of Interest," n.d.) or the University of Münster ("Studienfelder," n.d.). We derived the following ten groups:

- Medicine & Health
- Media & Communications
- Business & Economics
- Law
- Computer Science & Engineering
- Social Science
- Natural Science & Maths

- Language, Culture & History
- Arts & Design
- Other

Deviating from common groupings, we decided to split Business and Economics and Law into two distinct groups because of the predominance of business education in startup founders. Also, we distinguish between Computer Science and Engineering and Natural Science and Maths because the former has more application in a new venture, according to our sample. Again, the groups are coded with letters from A to J and each co-founder is allocated exactly one letter to form a team string, such as CEI. This string would represent a team of three with the first member to have a degree in Business & Economics, the second with a degree in Computer Science & Engineering and the third with a degree in Arts & Design.

The derivation of groups for the level of education is rather trivial because it is mostly predefined. Some countries show some peculiarities, such as the Diplom in the German education system. We defined four groups comprising one to four different types of degree (see Table 5-1):

Table 5-1

*Degrees and their ordinal levels / nominal groups.*

| | Level (ordinal) | Group (nominal) |
|---|---|---|
| Abitur, High School | 1 | A |
| Technical Diploma | 1 | A |
| Apprenticeship | 1 | A |
| Bachelor’s | 2 | B |
| Master’s | 3 | C |
| MBA | 3 | C |
| Diplom, Diploma | 3 | C |
| Staatsexamen | 3 | C |
| PhD | 4 | D |

Other than the measures described before, the level of education can be described by an ordinal and nominal value. In the forthcoming diversity calculation, only the nominal description is of interest but it is generally reasonable to formulate a hierarchy of degrees from high school, over Bachelor's and Master's to PhD degree, according to the Bologna Process.

## 5.3 Calculating Diversity

The calculation of diversity is rooted in the ecological literature, used primarily for biodiversity explorations to calculate the diversity in species of an ecosystem. However, the application of such metrics are not limited to ecological research but can be applied to any community or group that holds different types of members. In our dataset one company represents a community and the founders its members or "species" with four different characteristics, namely gender (F or M), functional experience (A to H), field of education (A to J), and level of education (A to D). Since no diversity index is dominant in the team diversity literature, we calculated two different indices for non-metric features and included them separately in the analysis.

First, the Shannon-Wiener index is a measure which quantifies the entropy in strings of text (Shannon, 1948). It follows the idea that the more diverse, i.e., different, letters are in a string of text, the more difficult it is to correctly predict the next letter in the string. The Shannon-Wiener index quantifies the uncertainty in this prediction. It is calculated as follows:

$$H' = -\sum_{i=1}^{R} p_i \ln p_i$$

where $p_i$ is the share of characters of the *i*th type of letter in the string and *R* the variety of letters in that string. A completely homogeneous community has a Shannon-Wiener index value of 0. A more diverse community has a higher score.

In the case of an exemplary gender diversity string, such as FFM, *R* equals 2 (F and M) and $p_i$ equals ⅔ and ⅓, for F and M respectively. Multiplying the natural logarithm of $p_i$ with $p_i$ results in -0.27 and -0.37 for F and M respectively. The sum of both values multiplied by -1 then equals 0.64 which is the diversity index for the team FFM. Equally, a team represented by MMF would have the same diversity index of 0.64. See Appendix G for an index values for various letter combinations.

Second, the Simpson index, also known as the Herfindahl index, is a measure of similar nature (Simpson, 1949). This measure equals the chance that two randomly taken entities from the dataset represent the same type. A completely homogeneous community has a Simpson index value of 1. The more diverse the community, the lower the Simpson index. The Simpson index is calculated similar to the Shannon-Wiener index, as follows. Here, *R* represents the richness or the total number of types and $p_i$ refers to the ratio of type i in the dataset:

$$\lambda = \sum_{i=1}^{R} p_i^2$$

The Simpson index is a dominance index as it gives more weight to common or dominant types or species. Compared to the Shannon index, the Simpson index increases less rapidly when adding species. Generally, the Simpson index is more sensitive to the evenness of species in the community.

For a scalable calculation of the diversity indices for all teams, we wrote an app script in JavaScript that runs in Google Sheets (see Appendix A). The result is nine diversity indices for each startup team which constitute the independent variables in the forthcoming analysis.

## 5.4 Models

As the previous subchapters established, the analysis consists of three dependent variables and two types of diversity indices with four diversity measures plus the age diversity as the standard deviation. Of course, not all combinations of variables can be analysed in a single model. Instead, we considered 6 different models shown in Table 5-2. For example, the success definition of model 4 is success1 (has exit) and the four diversity indices (gender, functional experience, field of education, level of education) are calculated as the Simpson index. Age diversity as the fifth independent variable is measured as the standard deviation in every model.

Table 5-2

*Different models with success definition and diversity index.*

| | Success definition (dependent variable) | Diversity index (independent variable) |
|---|---|---|
| Model 1 | success1 | Shannon |
| Model 2 | success2 | Shannon |
| Model 3 | success3 | Shannon |
| Model 4 | success1 | Simpson |
| Model 5 | success2 | Simpson |
| Model 6 | success3 | Simpson |

## 5.5 Descriptive Statistics

In total, the dataset included 495 co-founders in 178 new venture teams founded between 1988 and 2018. Of the 178 teams, 16.85% (n = 30) included at least one female co-founder, however only 6% (n = 30) of all founders are female. The average number of employees is 996.30 (SD = 1872.42). Most of all new ventures which have not exited were in Series D (n = 24), followed by Seed (n = 22), and Series B (n = 21). 38.76% (n = 69) of all ventures have exited either by acquisition (n = 49) or by IPO (n = 20). The sample included new ventures from 16 different European countries, however not equally distributed. Germany (38.2%, n = 68), UK (23.0%, n = 41), and France (9.6%, n = 17) were the countries with the most ventures in this sample. Some countries in the sample, such as Bulgaria, Estonia, and Lithuania only present a single venture. More statistics are described in Table 5-3.

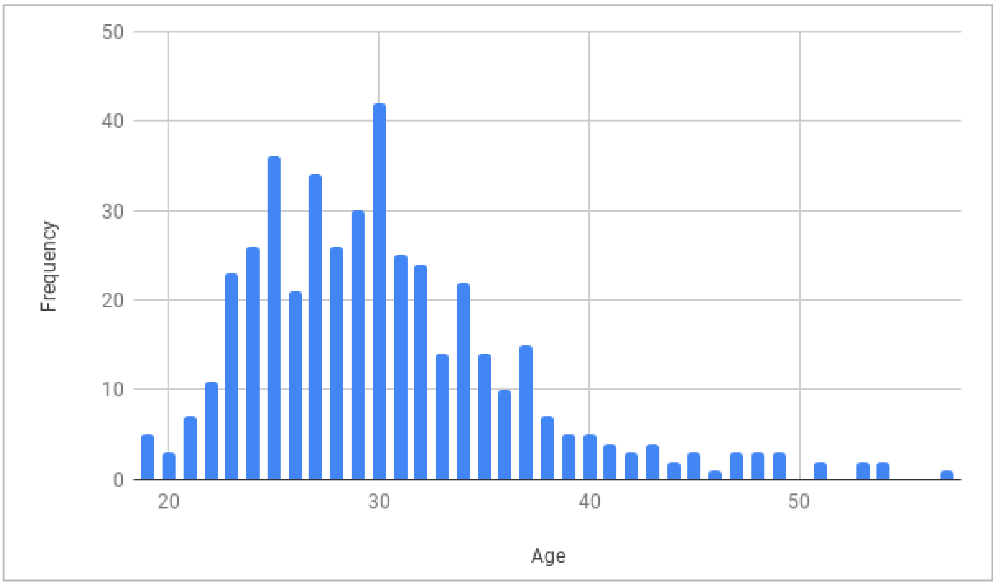
Table 5-3

*Descriptive statistics.*

| | N | Min | Max | Mean | Std. Dev. |
|---|---|---|---|---|---|
| Founding Year | 178 | 1988 | 2018 | 2009.49 | 5.445 |
| Co-Founders | 178 | 2 | 6 | 2.79 | 0.937 |
| Co-Founders’ Age | 439 | 19 | 57 | 30.29 | 6.583 |
| Funding (in $M) | 158 | 0 | 2800 | 120.78 | 285.538 |
| Series (coded) | 178 | 1 | 10 | 5.99 | 3.504 |
| Employees | 111 | 12 | 15000 | 996.30 | 1872.416 |
| Exit Year | 70 | 2001 | 2019 | 2013.63 | 3.849 |
| Years to Exit | 70 | 1 | 30 | 8.37 | 4.834 |
| Exit Value (in $M) | 55 | 0.36 | 6800 | 885.75 | 1435.321 |

Figure 5-2

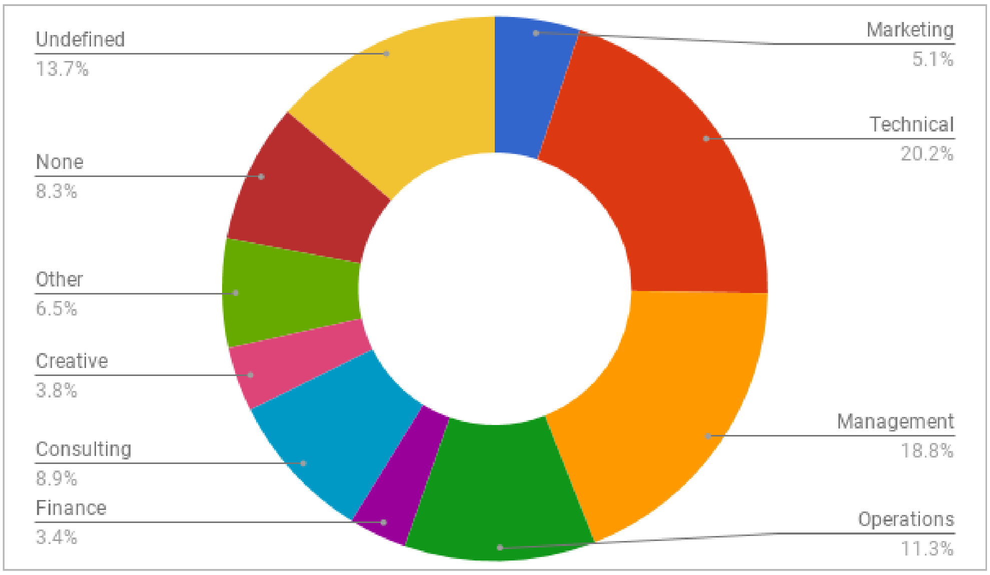
*Distribution of ages.*




The average age at the time of the foundation of a co-founder is 30.29 years (SD = 6.58), the youngest being 19 years old, the oldest 57. The most common age to start a venture is between the mid-20s to early-30s as Figure 5-2 shows.

Figure 5-3

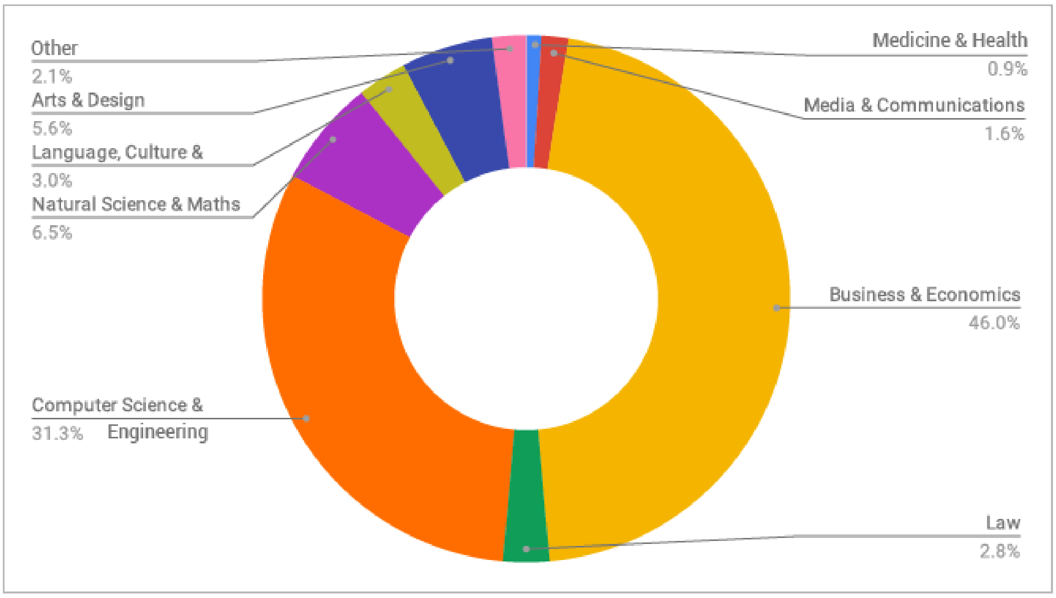
*Distribution of functional experiences.*




As visualized in Figure 5-3, most (n = 100) co-founders were identified to have a technical functional experience, second most (n = 93) a management and third most (n = 56) a operations experience.

Figure 5-4

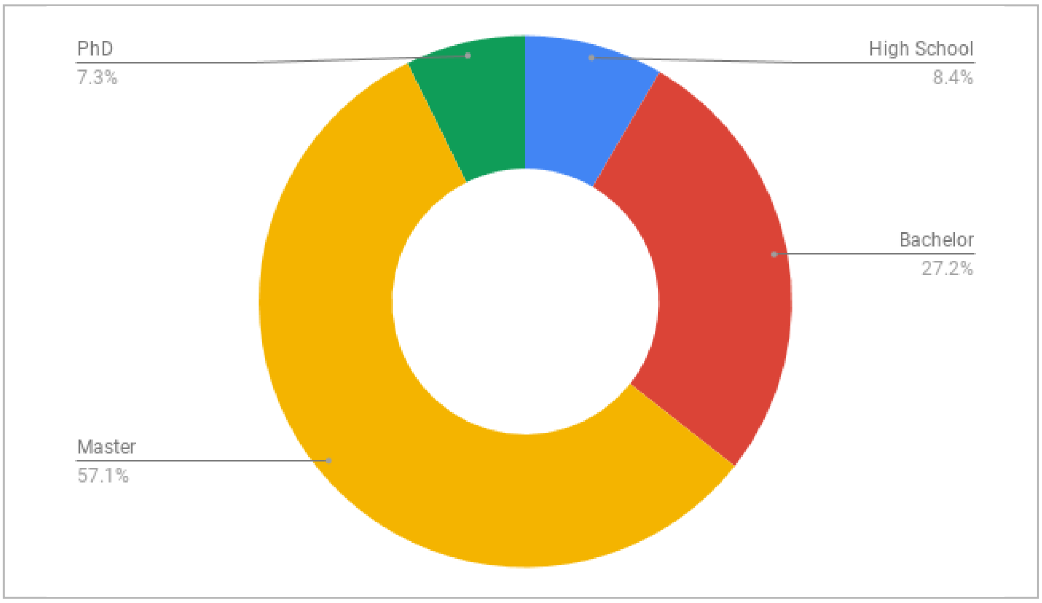
*Distribution of fields of education.*




Most (46%, n = 197) founders have a degree in Business and Economics, followed by Computer Science (31.3%, n = 134) and Natural Science and Maths (6.5%, n = 28) (see Fig. 5-4).

Figure 5-5

*Distribution of levels of education.*




The highest education of 57.1% (n = 258) of all founders is a Master's degree (or equivalent) and a Bachelor's degree of 27.2% (n = 123), as visualized in Figure 5-5. 8.4 % (n = 38) only have a high school diploma (or equivalent) and 7.3 % (n = 33) hold a PhD.

Figure 5-6

*Investments in million US-Dollars in the progression of stages.*


As Figure 5-6 shows, the increase in investments in the progression of stages follows an exponential trajectory. The average company collected 120.78 million US-Dollars in funding (SD = 285.54).

## 5.6 Logistic Regression

In this thesis, we are interested in the correlation between new venture success, defined from an external financing perspective, and the diversity of the founder team. To calculate such correlation, statistical regression is an appropriate means of analysis. We commence this subchapter with an explanation of different types of regression and conclude that the binomial logistic regression is applicable to answer our research question. Subsequently, we explain the binomial logistic regression more thoroughly and examine its assumptions before presenting the results of all previously defined models.

### 5.6.1 Regression Analysis

Regression analysis is a set of statistical processes that are applied to estimate the relationships of variables (Hastie et al., 2017). Given that the definition of success is of nominal nature (either successful or unsuccessful) and not a continuous value (such as funding in million US-Dollars), linear regression is not appropriate. Rather, we face a classification task. For this, a logistic regression (or logit model), is applicable. The logistic model can be *ordinal*, *multinomial*, or *binomial*. The nature of the dependent variable indicates the appropriate model. An *ordinal* logistic model can estimate the relationship between independent variables and a dependent variable that can be ordered, e.g., the results of a Likert scale *satisfied/neutral/not satisfied*, where *satisfied* is better than *neutral* and *not satisfied*. *Multinomial* logistic regressions are used when the dependent variable can take on multiple values without an order, such as *disease A/disease B/disease C*. Lastly, *binomial* logistic regression is applicable if the dependent variable can be one of two values such as *pass/fail*, *alive/dead*, or *win/loss* (dichotomous). This type of regression allows predicting the probability of an event occurring when only one of two independent outcomes are possible (Kohler & Kreuter, 2016). Thus, to test the significance of the difference in diversity between the two groups, successful and unsuccessful ventures, we model a binomial logistic regression.

## 5.6.2 Binomial Logistic Regression

### 5.6.2.1 Formula

Binomial logistic regression (or simply binomial regression) is one model of a group of tests called Generalized Linear Models (Weisberg, 2005). These models extend linear models to include dependent variables that are other than continuous, e.g., dichotomous. Equal to multiple regression, binomial regression calculates the relationship of multiple independent variables and a single dependent variable. Peculiar to the binomial regression, the dependent variable is dichotomous. Further, instead of predicting the category affiliation directly, a transformation is applied that predicts the logit of the dependent variable instead. A logit (or log-odds) is the natural logarithm of the odds of an event occurring. A binomial regression under consideration of the dependent variable $Y$ and $n$ independent variables $X_1$, $X_2$, ... $X_n$ has the following form (Laerd Statistics, 2015):

$$\mathrm{log}it(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon$$

where $\beta_0$ is the intercept (or constant), $\beta_n$ the slope parameter (or coefficient) for $X_n$, and $\varepsilon$ describes the errors. This population model can be approximated for the sample as follows:

$$\mathrm{log}it(Y) = b_0 + b_1 X_1 + b_2 X_2 + \ldots + b_n X_n + e$$

where $b_0$ is the sample intercept (or constant) that estimates $\beta_0$, $b_n$ the sample slope parameters (or coefficient) for $X_n$ that estimates $\beta_n$, and e approximates the errors $\varepsilon$.

#### 5.6.2.2 Assumptions

Setting up the binomial logistic regression, seven assumptions were considered of which the first three refer to the procedure design and later four to the nature of the data (Laerd Statistics, 2015). The satisfaction of these assumptions directly impact the validity of the analysis and the explanatory power of our findings and were therefore important to consider (Hayes, 2013). As described previously, the analysis comprises six different models, each representing a different combination of a success definition and a diversity index. The following assumptions were tested on all models.

The first assumption states that the only dependent variable must be dichotomous. This requirement is met since our success definition in binary. Second, one or more independent variables are measured on a continuous or nominal scale. This condition was met as the diversity measures are all continuous. Third, independence of observation was satisfied as the categories of dichotomous dependent variables are mutually exclusive and exhaustive. In other words, a single venture cannot be classified as both successful and unsuccessful. Assumption number four assumes a minimum of 15 observations per category. The dataset at hand complies with that. The fifth assumption requires a linear relationship between the continuous independent variables and the logit transformation of the dependent variable. To test for linearity, we apply the Box-Tidwell (1962) procedure. All interaction terms are statistically not significant, indicating that all continuous variables in the current model are linearly related to the logit of the dependent variable. Assumption number six assumes the data not to have any multicollinearity. To test this assumption, we modelled various linear regressions with only the independent variables which were iterated as the dependent variable in this model (see Appendix D). The variance inflation factor (VIF) ranged from 1.005 to 1.382, which indicates that multicollinearity was not a concern (Kohler & Kreuter, 2016). The seventh and last assumption requires no significantly biased outliers. The analysis shows at most five outliers with a standardized residual ranging from -5.278 to 2.530, depending on the model. We examined the respective cases for incorrectly entered or irregular values but found no meaningful argument to exclude the ventures from the analysis. Any unfounded omitting of cases would bias the model to overfit the sample which, in turn, would lead to less robust results.

### 5.6.2.3 Results

The following summarizes the results across all models (see Table 5-4). The range of cases that were included in the respective model lies between 50% (model 1, model 4, n = 89) and 78.21% (model 3, model 6, n = 140). The difference in the number of missing values results from the different success definitions. The accuracy for the base model that only includes the constant in the analysis is 62.9% for model 1 and 2, 76.3% for model 2 and 4, and 76.4% for model 3 and 6.

Table 5-4

*Testing assumptions for each model.*

| | Cases included | Base model accuracy | Model accuracy | Omnibus test sig. | Pseudo R (Nagelkerke) | Hosmer and Lemeshow test sig. |
|---|---|---|---|---|---|---|
| Model 1 | 89 | 62.90% | 92.13% | 0.000 | 0.848 | 1.000 |
| Model 2 | 139 | 76.30% | 87.05% | 0.000 | 0.627 | 0.642 |
| Model 3 | 140 | 76.40% | 87.14% | 0.000 | 0.628 | 0.639 |
| Model 4 | 89 | 62.90% | 89.89% | 0.000 | 0.844 | 1.000 |
| Model 5 | 139 | 76.30% | 89.21% | 0.000 | 0.625 | 0.903 |
| Model 6 | 140 | 76.40% | 88.57% | 0.000 | 0.626 | 0.901 |

To evaluate the predictive power of the binomial regression, we considered three indicators, namely the Omnibus Tests of Model Coefficients, the Nagelkerke's pseudo-$R^2$ and the Hosmer and Lemeshow Test (Laerd Statistics, 2015). First, the Omnibus Tests of Model Coefficients assesses the overall statistical significance of the model. More accurate, this test indicates the correctness of class affiliation prediction of the current model versus a model with no independent variables. The results show that all models are statistically significant on a 99.9% level (p = 0.0001).

Second, we calculated the explained variation of the model. In linear regression, $R^2$ is a common static to assess the explained variation and thus the goodness of fit. However, for a binomial regression, the common $R^2$ is not applicable. Instead, Nagelkerke's pseudo-$R^2$ is a modification of the common $R^2$ that is appropriate to assess the goodness of fit of logistic regression.

The non-pseudo-$R^2$ is a statistical measure that is calculated by an *ordinary least squares* regression. This statistic is often used to compare the goodness of fit of various models. It describes the ratio between the sum of squared differences between the actual and the predicted values in the numerator and the sum of squared differences between the actual values and their mean in the denominator:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}$$

Applicable for logistic regression, Nagelkerke's pseudo-$R^2$ describes the improvement from the null model to the fitted model. Here, the denominator of the ratio is equal to the sum of squared errors from the null model, that is, the model that predicts the dependent variable without the consideration of the independent variables. In the null model, all values are predicted to be the mean of the observations. In other words, if 70% (> 0.5) of the cases in the sample hold the value 1 for the dependent variable, in the null model, all values are predicted 1. The mean can be thought of the best guess without any information about the independent variables. The numerator of this ratio describes the sum of squared errors of the fitted model. Thus, the pseudo-$R^2$ indicates the degree to which the model fit increases as the results of the direct effects of the independent variables. The higher the pseudo-$R^2$, the greater the improvement.

The value for the Nagelkerke's pseudo-$R^2$ ranged between 0.625 (model 5) and 0.848 (model 1) which indicates that all models including the independent variables had a better fit than the base models without any independent variables. Thus, the explained variation in the dependent variable is between 62.5% and 84.8%.

Other than the common $R^2$ which assesses the increase in variation that is explained by adding additional variables to a linear regression model, Nagelkerke's pseudo-$R^2$ only provides an abstract indication whether the additional variables contribute towards an increase in the explained variation. Because of the abstract-nature of Nagelkerke's pseudo-$R^2$, we additionally included the Hosmer and Lemeshow test which estimates how poor the model is fitting. For all models, the Hosmer and Lemeshow test yielded non-significant values between 0.639 (model 3) and 1.000 (model 1 and 4), indicating that all models did not fit poorly.

Furthermore, we evaluated the sensitivity, specificity, and precision (see Table 5-5). The sensitivity (also recall or true positive rate) is the ratio of cases which are classified as successful and truly were successful (true positive) out of all as successful predicted cases (positives). Similarly, specificity (also selectivity or true negative rate) is defined as the ratio of cases which are classified as unsuccessful and truly were unsuccessful (true negative) out of all as unsuccessful predicted cases (negatives). Lastly, precision is defined as the ratio of all true positives out of all cases. As Table 5-5 shows, model 1 has the highest accuracy with 92.13% correctly predicted cases and model 2 has the lowest accuracy with 87.05%.

Table 5-5

*Classification values for all models.*

| | True Positives | True Negatives | False Positives | False Negatives | Accuracy | Sensitivity | Specificity | Precision |
|---|---|---|---|---|---|---|---|---|
| Model 1 | 54 | 28 | 2 | 5 | 92.13% | 91.53% | 93.33% | 96.43% |
| Model 2 | 99 | 22 | 7 | 11 | 87.05% | 90.00% | 75.86% | 93.40% |
| Model 3 | 100 | 22 | 7 | 11 | 87.14% | 90.09% | 75.86% | 93.46% |
| Model 4 | 54 | 26 | 2 | 7 | 89.89% | 88.52% | 92.86% | 96.43% |
| Model 5 | 100 | 24 | 6 | 9 | 89.21% | 91.74% | 80.00% | 94.34% |
| Model 6 | 101 | 23 | 6 | 10 | 88.57% | 90.99% | 79.31% | 94.39% |

In the following, the odds ratio (OR) refers to the exponentiation of the B coefficient (Exp(B)). We use the odds ratio here because it can be easier to interpret than the coefficient B which is in log-odds units. For example, a one-unit increase in age diversity increases the odds of a venture being classified as successful in this model by a factor of 1.444, i.e., 44,4%. The lower and upper values for the 95% C.I. for Exp(B) describe the boundaries of the respective coefficient in a 95% confidence interval. In other words, the model shows that with 95% confidence the OR of a measure will fall into this range, e.g., for age diversity in model 1 between 0.759 and 2.622. The column labelled *Sig.* in the following tables describe the level of statistical significance which is denoted by p in the text. The smaller this number, the higher the significance, that is, the more certain this effect.

Table 5-6

*Direct effects of age diversity across all models.*

| | | | | 95% C.I. for Exp(B) | |
|---|---|---|---|---|---|
| | B | Sig. | Exp(B) | Lower | Upper |
| Model 1 | 0.344 | 0.277 | 1.411 | 0.759 | 2.622 |
| Model 2 | 0.359 | 0.083 | 1.432 | 0.954 | 2.151 |
| Model 3 | 0.364 | 0.075 | 1.439 | 0.964 | 2.147 |
| Model 4 | 0.292 | 0.298 | 1.339 | 0.772 | 2.321 |
| Model 5 | 0.361 | 0.078 | 1.435 | 0.960 | 2.144 |
| Model 6 | 0.365 | 0.071 | 1.440 | 0.969 | 2.141 |

As Table 5-6 shows, the significance for age diversity range between 70.2%[1] (model 4, p = 0.298) and 92.9% (model 6, p = 0.071). There is a distinct difference in the significance between models 1 and 4 which share the same success metric and the other models that have a similar success metric. The OR is stable with an average of 1.416 and a standard deviation of 0.039.

Table 5-7

*Direct effects of gender diversity across all models.*

| | | | | 95% C.I. for Exp(B) | |
|---|---|---|---|---|---|
| | B | Sig. | Exp(B) | Lower | Upper |
| Model 1 | -0.048 | 0.984 | 0.953 | 0.009 | 106.154 |
| Model 2 | -2.929 | 0.060 | 0.053 | 0.003 | 1.130 |
| Model 3 | -2.933 | 0.060 | 0.053 | 0.003 | 1.129 |
| Model 4 | 0.002 | 1.000 | 1.002 | 0.002 | 523.851 |
| Model 5 | 3.971 | 0.072 | 53.052 | 0.705 | 3990.876 |
| Model 6 | 3.976 | 0.072 | 53.314 | 0.706 | 4025.143 |

Models 2, 3, 5, and 6 attribute gender diversity a significant influence on a 94%, 94%, 92.8%, and 92.8% significance level, respectively (see Table 5-7). Contrary, models 1 and 4 show no significance for gender diversity. Models 1 and 4 attribute gender diversity no effect (0.952 < OR < 1.002). Contrary, in the other models, gender diversity has a stark influence on the model. Note for the interpretation of the results of models 4, 5, and 6 that, other than the Shannon index, the here applied Simpson index reflects a lower value for higher diversity.

[1] Calculated as 1-p = 1-0.298 = 0.702

This means that the values for B must be multiplied with -1 and Exp(B) must inverted (1/Exp(B)) to be directly comparable with models 1, 2, and 3. With the highest OR, model 6 yields a value of 53.314. This means that a one-unit increase in gender diversity would result in a decrease in odds being classified as successful by a factor of 53.314. To put this value into context, a team that has odds of, e.g., 0.8 being classified as successful increases its gender diversity by 0.1. This would result in a decrease in odds being classified as successful to 0.15[2].

Table 5-8

*Direct effects of functional diversity across all models.*

| | | | | 95% C.I. for Exp(B) | |
|---|---|---|---|---|---|
| | B | Sig. | Exp(B) | Lower | Upper |
| Model 1 | -1.728 | 0.252 | 0.178 | 0.009 | 3.408 |
| Model 2 | 0.585 | 0.542 | 1.795 | 0.273 | 11.782 |
| Model 3 | 0.589 | 0.540 | 1.802 | 0.274 | 11.830 |
| Model 4 | 1.899 | 0.398 | 6.681 | 0.081 | 548.122 |
| Model 5 | -1.329 | 0.363 | 0.265 | 0.015 | 4.624 |
| Model 6 | -1.333 | 0.361 | 0.264 | 0.015 | 4.608 |

No model shows any significance for functional diversity, ranging from 46% (model 3, p = 0.540) to 74.8% (model 1, p = 0.252) (see Table 5-8). Also, the OR is not consistent across models. Thus, functional diversity does not have a direct effect on the venture success classification.

Table 5-9

*Direct effects of field of education diversity across all models.*

| | | | | 95% C.I. for Exp(B) | |
|---|---|---|---|---|---|
| | B | Sig. | Exp(B) | Lower | Upper |
| Model 1 | 0.761 | 0.661 | 2.140 | 0.071 | 64.484 |
| Model 2 | 1.181 | 0.204 | 3.258 | 0.526 | 20.187 |
| Model 3 | 1.178 | 0.206 | 3.247 | 0.524 | 20.124 |
| Model 4 | -0.720 | 0.766 | 0.487 | 0.004 | 55.224 |
| Model 5 | -1.501 | 0.264 | 0.223 | 0.016 | 3.102 |
| Model 6 | -1.498 | 0.265 | 0.224 | 0.016 | 3.114 |

[2] Calculated as 0.8 * (1 / (53.314 * 0.1))

Similarly, field of education diversity shows no significant effect across all models with values for the significance ranging from 23.4% (model 4, p = 0.766) to 79.6% (model 2, p = 0.204) (see Table 5-9). The leading sign for the coefficient is congruent but the values fluctuate. Thus, field of education diversity does not seem to have a direct influence on the classification of venture success.

Table 5-10

*Direct effects of level of education diversity across all models.*

| | | | | 95% C.I. for Exp(B) | |
|---|---|---|---|---|---|
| | B | Sig. | Exp(B) | Lower | Upper |
| Model 1 | 0.164 | 0.918 | 1.179 | 0.051 | 27.166 |
| Model 2 | 0.496 | 0.558 | 1.643 | 0.312 | 8.649 |
| Model 3 | 0.491 | 0.562 | 1.634 | 0.311 | 8.597 |
| Model 4 | 0.056 | 0.980 | 1.057 | 0.014 | 78.446 |
| Model 5 | -0.588 | 0.627 | 0.556 | 0.052 | 5.957 |
| Model 6 | -0.582 | 0.631 | 0.559 | 0.052 | 5.988 |

Further, level of education diversity also has no significant influence on the model (see Table 5-10). Here, the leading sign and the values are unsteady. Again, we can conclude that level of education diversity has no influence on the classification.

Included in the models are two control variables, namely the number of co-founders and the founding year as a categorical value, none of which have a significant influence on the model (see Tables 5-11 and 5-12).

Table 5-11

*Direct effects of number of co-founders (control) across all models.*

| | | | | 95% C.I. for Exp(B) | |
|---|---|---|---|---|---|
| | B | Sig. | Exp(B) | Lower | Upper |
| Model 1 | 0.044 | 0.926 | 1.045 | 0.413 | 2.643 |
| Model 2 | -0.231 | 0.526 | 0.794 | 0.388 | 1.622 |
| Model 3 | -0.234 | 0.519 | 0.791 | 0.388 | 1.613 |
| Model 4 | -0.006 | 0.990 | 0.994 | 0.403 | 2.452 |
| Model 5 | -0.210 | 0.555 | 0.811 | 0.404 | 1.626 |
| Model 6 | -0.213 | 0.548 | 0.809 | 0.404 | 1.618 |

Table 5-12

*Direct effects of founding year (control) across all models.*

| | Sig. |
|---|---|
| Model 1 | 1.000 |
| Model 2 | 0.684 |
| Model 3 | 0.684 |
| Model 4 | 1.000 |
| Model 5 | 0.667 |
| Model 6 | 0.666 |

## 5.7 Survival Analysis

Following the abductive research approach in this thesis, we want to integrate the survival analysis to challenge the results from the logistic regression. We reason that only the congruence of both means of analysis for the respective measure would confirm a true influence on the success or failure of a venture. In the following, we describe the background of survival and hazard analysis, test assumptions, and eventually presents the results of this model. Also, we present relevant limitations to this model. The discussion of the results and the comparison with the results from the logistic regression will follow in the discussion.

### 5.7.1 Background

New ventures share some resemblance to patients with a serious medical condition: most die and only a few survive over time. In medical research, the analysis of death or survival provoked by certain condition or hazard is called survival analysis (Kleinbaum & Klein, 2010). Following this notion, new ventures could be described as infested and one could analyze the survival or death in equal manner.

Survival analysis refers to a set of statistical approaches applied to assess the time it takes for an event, e.g., death, to occur (Kleinbaum & Klein, 2010). Although most prominently used in medical research, survival analysis also finds appropriate use in social science for event-history analysis or in engineering for failure-time analysis (Hutchison, 1988). Survival analysis focuses on the expected duration until the occurrence of an event. However, the event may have only occured in some cases within the period of investigation, leaving so-called censored observations. For example, following the description of new ventures, a venture that has not failed in Series A may still fail at a later-stage.

The two related probabilities, namely, *survival probability* and *hazard probability* are used to describe survival data. The former, also known as the survivor function *S(t)* describes the probability that an individual survives from the time of diagnosis to a specific point in time *t* in the future. Reverse, the hazard probability *h(t)* describes the probability that a certain event, e.g., death, occurs to an individual.

One commonly-used method used to estimate the survival probability is the Kaplan-Meier method (Kaplan & Meier, 1958). This method is univariate, which means that it only assesses the survival probability according to a single factor under investigation. An alternative method is the Cox proportional-hazard model (Cox, 1972). This regression model extends other survival analysis methods to account for multiple predictor (i.e., independent) variables. As such, it is similar to a logistic regression but additionally factors in the time when an event occurs. This makes the Cox proportional-hazard model an appropriate model for the analysis of new ventures which "die" at different stages.

In the following we conceptually compare the course of disease of a human patient with the life cycle of a venture. Both progresses share the occurrence of an event, that is, e.g., death for the patient, and cease from operation for a venture. This event befalls at a certain point in time. For the patient, this point can simply be measured by the time that has passed since the diagnose or in stages, e.g., A, B, C, D. Similarly, for a venture, we assume the financing rounds (Seed, Series A, ..., Exit) to resemble the stage of a disease. Hereby, we disregard the actual time but focus on the progress itself. In other words, we ignore the time that has passed between the founding of a venture and its death but take the stages instead. We can do that because the progress is sequential; by definition Series B comes after Series A and Seed. Also, a series cannot be skipped (expect when a venture exits, which is not a hazard event). The results must be interpreted accordingly: This model does not conclude on the age of a venture (in time) but its progression in the life cycle (in rounds). As the results will show, contrary to the intuitive progress of a disease with the chance of the event occurring increasing with time, for ventures, we see that the chance of insolvency is highest in the early stages and decreases progressively. Applying this concept, we are able to construct a time-dependent model on cross-sectional data because every venture itself presents a time- (or stage-) dependent observation.

### 5.7.2 Cox Proportional-Hazards Model

#### 5.7.2.1 Hazard Function

The Cox model is described by a hazard function *h(t)* that expresses the risk of an event occurring, e.g., death, at time *t* under consideration of multiple independent variables, called covariates in the survival analysis (Kleinbaum & Klein, 2010). It is denoted as follows:

$$h(t) = h_0(t) \times exp(b_1x_1 + b_2x_2 + \ldots + b_px_p)$$

where $x_1, x_2, \ldots, x_n$ represent the covariates and $b_1, b_2, \ldots, b_n$ measure the impact of the covariates. $h_0$ describes the baseline hazard that estimates the hazard if all covariates are 0.

The hazard function resembles a multiple linear regression with the logarithm of the hazard as a linear function of their static covariates with the intercept corresponding to the baseline hazard that changes over time. The quantifiers $exp(b_i)$ are called hazard ratios (HR). A HR greater than 1 (equals $b_i$ greater than 0) indicates an increase in the probability of the event occurring and a decrease in the probability of survival. Vice versa, a HR lower than 1 indicates a reduction in the hazard. A HR of 1 indicates no effect.

#### 5.7.2.2 Assumptions

The Cox model makes three assumptions (Moore, 2016). The first assumption is that the HR of two subjects are proportional and thus remain the same at all times. The term *proportional hazard* refers to the assumption of a constant relationship between the dependent variable and the covariates (Moore, 2016). This means that two distinct hazard curves are proportional and cannot cross. The *check_assumptions* function of the lifelines package checks this first assumption (Davidson-Pilon et al., 2019). This test yields no warnings in our analysis. The second assumption requires no influential observations or outliers. To test this assumption we calculate the Deviance residual and examine the visualization. The plot shows a bias to higher residuals for series one and two and a bias to negative residuals for series four to seven but shows no influential outliers. The reason for this skew is the imbalance in the dataset which features more failed ventures in the early stages than failures in later stages. This reflects the higher failure ratio in early ventures compared to later-stage ventures. The third and final assumption assumes linearity between the log hazard and the covariates. To test this assumption we calculate and plot the Martingale residual and conclude no linearity.

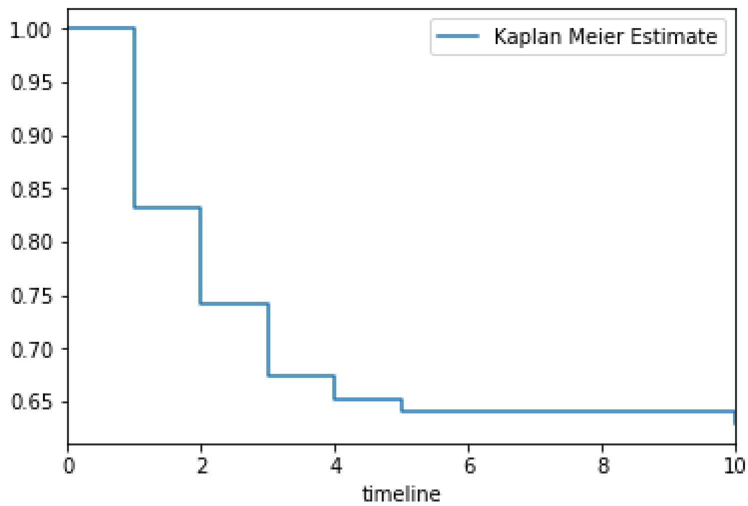
#### 5.7.2.3 Results

In the following, the results of a Kaplan-Meier model and of the Cox proportional-hazards model is described. The strength of the hazard analysis is the consideration of a time- or stage-dependent process which can be described by the stage or series of a venture (Seed, Series A, ..., Exit). Notably, the event of interest in the hazard analysis is not survival but death. Representative for this event in this analysis is the inverse of the previously established success definitions. In other words, ventures that were coded as successful in the previous analysis are now defined to hold no event (0: survival) and the other ventures – according to the respective success/failure definition – now hold the event (1: failure).

The Kaplan-Meier model (Kaplan & Meier, 1958) allows to visualize of the survival progression estimate (see Figure 5-7). The ordinate describes the probability of survival. The abscissa describes the various series on a timeline. For example, a venture in series 2 is predicted to have a survival rate of 75% according to this model. This model does not consider the diversity indices but only the event and the time it occurs.

Figure 5-7

*Kaplan-Meier estimate for model 2 (variant).*



Extending the Kaplan-Meier model, we apply a Cox proportional-hazard model using the *CoxPHFitter* function of the lifelines package which yields the following results (see Table 5-13). Similar to the logistic regression, this model considers the diversity covariates individually.

Table 5-13

*Direct effects of covariates on new venture failure in the Cox proportional-hazard model.*

| | | | | 95% C.I. for Exp(B) | |
|---|---|---|---|---|---|
| | B | Sig. | Exp(B)[3] | Lower | Upper |
| Age diversity | | | | | |
| Model 1 | -0.285 | 0.019 | 0.752 | -0.522 | -0.048 |
| Model 2 | -0.282 | 0.024 | 0.754 | -0.527 | -0.037 |
| Model 3 | -0.283 | 0.022 | 0.753 | -0.527 | -0.040 |
| Model 4 | -0.285 | 0.018 | 0.752 | -0.522 | -0.049 |
| Model 5 | -0.286 | 0.023 | 0.751 | -0.532 | -0.040 |
| Model 6 | -0.288 | 0.021 | 0.750 | -0.533 | -0.043 |
| Gender diversity | | | | | |
| Model 1 | 1.129 | 0.162 | 3.094 | -0.454 | 2.713 |
| Model 2 | 1.390 | 0.064 | 4.013 | -0.079 | 2.858 |
| Model 3 | 1.391 | 0.063 | 4.019 | -0.078 | 2.860 |
| Model 4 | -1.457 | 0.198 | 0.233 | -3.678 | 0.763 |
| Model 5 | -1.823 | 0.084 | 0.162 | -3.892 | 0.246 |
| Model 6 | -1.825 | 0.084 | 0.161 | -3.894 | 0.244 |
| Functional Diversity | | | | | |
| Model 1 | 1.207 | 0.019 | 3.343 | 0.202 | 2.211 |
| Model 2 | 0.507 | 0.303 | 1.661 | -0.459 | 1.473 |
| Model 3 | 0.507 | 0.303 | 1.661 | -0.458 | 1.473 |
| Model 4 | -1.744 | 0.026 | 0.175 | -3.280 | -0.209 |
| Model 5 | -0.746 | 0.324 | 0.474 | -2.227 | 0.735 |
| Model 6 | -0.746 | 0.323 | 0.474 | -2.227 | 0.735 |
| Field of education diversity | | | | | |
| Model 1 | -0.999 | 0.074 | 0.368 | -2.096 | 0.099 |
| Model 2 | -0.927 | 0.075 | 0.396 | -1.946 | 0.092 |
| Model 3 | -0.928 | 0.075 | 0.396 | -1.947 | 0.092 |
| Model 4 | 1.251 | 0.125 | 3.492 | -0.347 | 2.848 |
| Model 5 | 1.208 | 0.112 | 3.346 | -0.281 | 2.696 |
| Model 6 | 1.209 | 0.112 | 3.349 | -0.280 | 2.698 |

[3] In this model, the *Exp(B)* value describes the hazard ratio (HR) which is similar to the OR.

Since the event description is not success, as in the logistic regression, but failure, the coefficients must be interpreted accordingly. A positive value for *B* describes an increase in the probability of failure, whereas a negative value describes a decrease in the probability of failure. For example, age diversity ($0.018 < p < 0.024$) has a negative coefficient value ($-0.288 < B < -0.282$) which describes a negative influence on the event, i.e., failure, occurring. A one-unit increase in age diversity would yield a decreased baseline hazard by a factor of $0.750 < HR < 0.754$, that is, a decrease by approximately 25%. An HR greater than 1 has a positive impact on the hazard, an HR smaller than 1 has a negative impact on the hazard and a value of 1 has no impact.

Table 5-12 shows the covariates, i.e., independent variables, in the Cox model that display some significance. The other two variables, namely level of education diversity ($0.532 < p < 0.652$) and the number of co-founders ($0.847 < p < 0.977$) show no significance across all models (see Appendix H). The models yield the result that age diversity ($0.018 < p < 0.024$) is significant on a 97-98%-level. The effect of age diversity is negative on the hazard. In other words, a higher age diversity contributes positively to the survival of a venture. The results are not as distinct for gender diversity ($0.064 < p < 0.198$). Models 2, 3, 5, and 6 report gender diversity to have a significant influence on the model ($0.064 < p < 0.084$) on a 91-93%-level. Models 1 and 3, which have the narrower success/failure definition 1 (has exit) as their dependent variable, report no significance for age diversity ($0.162 < p < 0.198$). Across all models, the direct effect of gender diversity is positive towards the hazard ratio, i.e., increased gender diversity correlates negatively with the survival of a venture. Conversely, only models 1 and 4 show significance for functional diversity ($0.019 < p < 0.026$) whereas models 2, 3, 5, and 6 attribute no significance to this variable ($0.303 < p < 0.324$). All models agree on the direction of the effect which is positively correlated with the hazard. In other words, an increase in functional diversity reduces the chance of survival for a venture. The models are more in agreement regarding field of education diversity ($0.074 < p < 0.125$). Models 1, 2, and 3 yield a significant value for field of education diversity ($0.074 < p < 0.075$) on a 92.5%-level. Models 4, 5, and 6 show no significance ($0.112 < p < 0.125$). Model 1 to 6 show the same direction for the effect of field of education diversity which is negatively correlated with the hazard, in other words, an increase in field of education diversity would increase the chance of survival.

Figures 5-8 and 5-9 show a visualization of the direct effect of the coefficient on the hazard ratio on a 95%-confidence interval for models 1, and 2. The comparison shows the contrast of the effect of some variables. For example, model 1 shows gender diversity to have the biggest influence on the model whereas model 2 attributes functional diversity the strongest influence (see the rectangular box in the middle of the line for each variable). Also, the range of the C.I., visualized by the horizontal lines behind the rectangular boxes vary distinctively and is smallest for age diversity and largest for gender diversity. This shows the (un)certainty in the effect on the model. Again, a high value (a box further to the right) indicates a positive influence of this coefficient on the model, i.e., on the hazard. A lower value (a box further to the left) indicates a negative influence on the model, i.e., on the hazard.

Figure 5-8

*Visualisation of the coefficients' hazard ratio on a 95%-C.I. in the Cox model for model 1.*

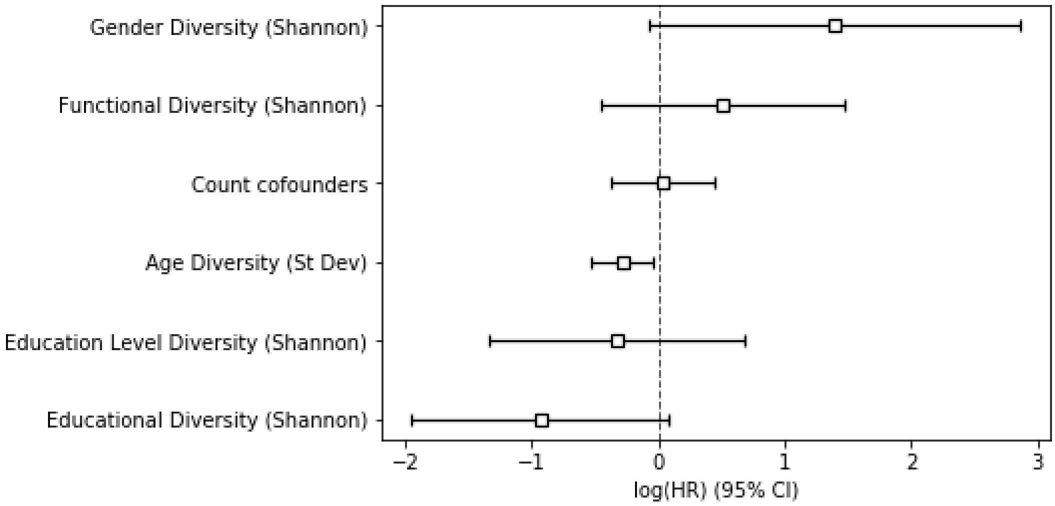
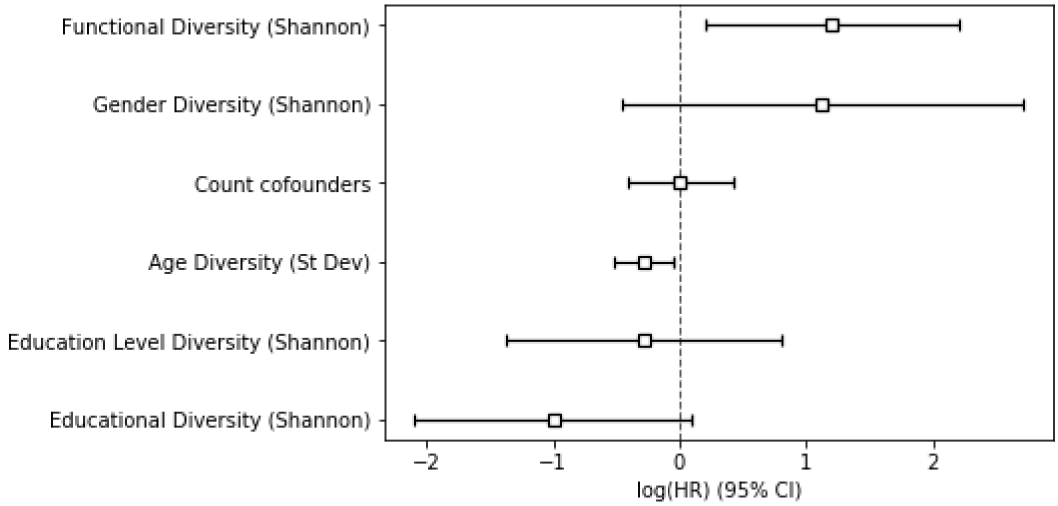


Figure 5-9

*Visualisation of the coefficients' hazard ratio on a 95%-C.I. in the Cox model for model 2.*




#### 5.7.2.4 Limitations

Some limitations apply to the hazard analysis. Notably, the success definition 1, applied in models 1 and 4, define success as "has exit" which is the same stage. Thus, no other venture in any other series can be successful by this definition. All failure definitions comprise the same cases of failed ventures. However, the cases of successful ventures differ. Although the hazard analysis is primarily concerned with the event occurring (failure), the strict definition of success and failure in models 1 and 4 which omits all ventures from Series B on that have no exit, might cause an imbalance and impair the generalizability of the results for models 1 and 4. Another limitation of the hazard analysis is the exclusion of the second control variable which is the year of foundation as a categorical variable. Including this variable in the Cox model inhibits the model from converging. Acknowledging this drawback, the results from the Cox model must primarily serve as a means to verify or falsify the results from the logistic regression and not to establish new insights by itself.

# 6 Qualitative Analysis

After calculating the direct effects of the various diversity factors, in this chapter we test the results using qualitative case study. Researchers agree that both diversity and VC decision-making are complex concepts. Hence, the derivation of quantitative measures alone to conclude on the relationship between the concepts cannot suffice. This reasoning mirrors the abductive research philosophy we apply in this thesis. This research approach calls for a multi-level analysis process in which insights generated in one means of analysis are not blindly trusted but tested and compared with other models and their results. To comply with this requirement and to draw a robust conclusion, in this chapter, we analyze representative ventures to estimate first, if diversity can be attributed a uni-directional effect and second, if the results from the quantitative analysis are universally applicable and decisive for VC-backed venture success and failure.

## 6.1 Analysis Process

In the first set of cases, we explore the relationship of diversity in the founding team and success and failure in general. First, Klarna represents a venture that is highly successful from the perspective of a VCF and that shows overall low diversity in the founding team. Contrary, Spoitify's founding team is diverse on most measures and also highly successful. The other way around, Cookies is a venture that is low in diversity and failed and Bullet is a venture that is high in diversity and also failed. In the upcoming discussion in chapter 7, we will explore reasons for the seemingly insignificant role diversity plays in these cases.

Taking the results from the quantitative analysis into consideration, we hypothesize that a team that is low in gender diversity and high in age diversity must be successful and conversely, a team that is high in gender diversity and low in age diversity must be unsuccessful, ignoring other diversity measures because they are insignificant according to the results of the quantitative analysis. In the second set of cases, we examine companies that show this configuration. Uberchord and again, Spotify represent the hypothesized successful combination of diversity factors and, on the other side, Lendstar and Unruly represent the hypothesized unsuccessful combination of diversity factors.

In this case study, we deliberately chose cases that represent ventures with a particular combination of level of diversity and success or failure. Of course, every venture is unique, thus, this case study cannot be exhaustive. Probably, for every hypothesis one will find a venture that agrees and another one that disagrees, potentially leading to confirmation bias. We acknowledge this drawback that is inherent to case studies and interpret the findings accordingly. In the case study we see a valuable addition to the quantitative analysis because we can examine particular cases more thoroughly and uncover previously disregarded factors that might extend our comprehension of the interplay of diversity and venture success and failure.

## 6.2 Case Company Description

In the following, we describe the background, progression, and team diversity of the selected ventures in detail. All teams described in the following are part of our existing dataset and thereby part of the quantitative analysis. The information we present here extend our dataset with information from other online sources, such as blog articles, company websites, and news articles. The plain descriptions of cases in this subchapter follows a summary of the results in the next subchapter. The discussion of the findings follow in the discussion in chapter 7.

### 6.2.1 Klarna

Klarna was founded in 2005 by Sebastian Siemiatkowski, Niklas Adalberth, and Victor Jacobsson in Stockholm, Sweden (Weverbergh, 2012). The company's core product is an online payment system that offers online shoppers the possibility to complete a purchase online by providing only a few information. Klarna assesses credit risk of online shoppers in the background and takes a transaction fee from merchants for underwriting the financial risk of the payment.

In mid-2005, the company received 60,000 Euro in Seed funding from an angel investor to build the initial product. Klarna achieved to become cash-flow positive in 2006 (Weverbergh, 2012). In December 2007 the company raised a 2 Million Euro Series A from Investment AB Öresund, a Swedish investment company, and in May 2009 a 9 Million Series B from Sequoia Capital, a US-based VCF (Schonfeld, 2011a). In December 2010 the VCF General Atlantic led a 155 Million Series C investment in Klarna (Schonfeld, 2011b). In 2013 Klarna acquired the German payment network Sofort for 150 million US-Dollars (Cutler, 2013). In later rounds, the company received additional funding from late stage VCFs and PE investors such as Permira and strategic investors such as Visa and H&M (Lunden, 2018).

To date, the company has raised a total of 791 Million US-Dollars in equity funding and is valued at 5.5 billion US-Dollars (Etherington, 2019). Klarna is currently active in 14 markets with 2,500 employees and has partnered with over 130,000 merchants and generated a revenue of 627 million US-Dollars in 2018 (Klarna, 2019).

The founding team's educational diversity can be considered low, both in terms of level of education as well as field of education: all three founders graduated in the same year from the same Master's program in Economics at the Stockholm School of Economics (Weverbergh, 2012). With regards to the founders' functional experience, none of them held a full-time position prior to founding Klarna. Since the founders are of the same age, age diversity can be considered low, too. Similarly, the gender diversity is low as all three co-founders are male. An overview of the attributes of interest can be found in Table 6-1.

Table 6-1

*Venture team diversity – Klarna.*

| | Sebastian Siemiatkowski | Niklas Adalberth | Victor Jacobsson | Level of Diversity[4] |
|---|---|---|---|---|
| Field of education | Economics | Economics | Economics | Low |
| Level of education | Master's | Master's | Master's | Low |
| Functional experience | None, only internships | None, only internships | None, only internships | Low |
| Gender | Male | Male | Male | Low |
| Age at founding | 24 | 24 | 24 | Low |

Klaus Hommels, general partner at Lakestar, a VCF that has invested in Klarna, stated in an interview that Klarna developed a competitive advantage by being able to analyse hundreds of parameters determining the credit risk of a user in real-time (Scott, 2014). Notably, no co-founder had any industry experience or experience in data science prior to founding the company (Weverbergh, 2012).

In an interview, Adalberth, a co-founder of Klarna, mentioned that the co-founders share a number of experiences. First, Adalberth and Siemiatkowski attended the same high school where they already met in 7th grade (Weverbergh, 2012). Years later, they worked together at

[4] The values low/mid/high refer to the averages we calculated in our dataset (see Appendix F in combination with Appendix G).

Burger King, a fast food chain, parallel to pursuing their Bachelor's degree in Economics at the Stockholm School of Economics. In 2002, Adalberth and Siemiatkowski went together on a world trip, before starting to study together with their then-future co-founder Jacobsson (Weverbergh, 2012).

### 6.2.2 Spotify

Spotify was founded in 2006 by Daniel Ek and Martin Lorentzon in Stockholm, Sweden ("Spotify company information, funding & investors", n.d.). The company offers an audio streaming platform for music and podcasts. Ek had the idea of what became Spotify when he realized that the file-sharing site Napster and similar services failed to compensate the music industry appropriately (Neate, 2010).

Spotify launched its product in 2008, after spending more than two years on the development of the product and negotiations with music industry representatives (Pärson, 2018). As the company was struggling to convince potential investors, Ek and Lorentzon invested their own money in the company (Bertoni, 2012). After the product launch in 2008, Spotify received 21.6 million US-Dollars in Series A funding from Creandum, Northzone, and other VCFs ("Spotify company information, funding & investors", n.d.). A Series B investment of 50 million US-Dollars from Wellington Partners and Horizons Ventures, two VCFs, was followed by an 11 million US-Dollars Series C in March 2010 from Founders Fund, a VCF, and Napster founder Sean Parker (Turula, 2018). In additional funding rounds, the company raised approximately 977 million US-Dollars in sum under the participation of VCFs, such as Accel Partners, and banks, such as Goldmann Sachs ("Spotify company information, funding & investors", n.d.). In 2018 Spotify issued an IPO at a firm valuation of 29.5 billion US-Dollars ("Spotify company information, funding & investors", n.d.). Today Spotify has over 230 million users across 79 markets ("Spotify company information, funding & investors", n.d.).

The team has high educational diversity. While Ek dropped out from university during the first semester of his undergraduate studies at Stockholm's Royal Institute of Technology (Bertoni, 2012), Lorentzon received a Master of Science in Civil Engineering from the Chalmers University (Plaza, 2015). The team's functional experience is high. Before Ek founded Spotify, he primarily worked as a freelance software engineer (Bertoni, 2012). Lorentzon worked for six years on the business side as the CEO and founder of Tradedoubler, a company that went public in 2005 (Bertoni, 2012). The age diversity can be considered high: at the time Ek and Lorentzon founded the company, Ek was 26 years old and Lorentzon was 37 years old. Since both founders are male, gender diversity is low. An overview of the attributes of interest can be found in Table 6-2.

Table 6-2

*Venture team diversity – Spotify.*

| | Daniel Ek | Martin Lorentzon | Level of Diversity |
|---|---|---|---|
| Field of education | None | Engineering | High |
| Level of education | High School | Master's | High |
| Functional experience | Technical | Management | High |
| Gender | Male | Male | Low |
| Age at founding | 26 | 37 | High |

A notable feature that emerges from this case is that Spotify's founding team has prior founding experience. Lorentzon received 70 million US-Dollars selling his Tradedoubler shares and Ek had already earned over 1 million US-Dollars through selling a software he programmed for Tradedoubler (Bertoni, 2012). Further, Ek and Lorentzon are also good friends since three years before founding Spotify (Bertoni, 2012). With regards to industry experience, neither Ek nor Lorentzon were familiar with the music industry prior to founding Spotify (Bertoni, 2012).

### 6.2.3 Cookies

Cookies was founded in February 2015 by Garry Krugljakow and Lamine Cheloufi in Berlin, Germany. The company offered a mobile app for transferring money between users ("Cookies App company information, funding & investors", n.d.).

Before launching its app, the company received a Seed investment from VCF Holtzbrinck Ventures and notable Seed investors such as Ehssan Dariani, the founder of the social network StudiVZ, and Chad Fowler, founder of the task management application Wunderlist (Krugljakow, 2016).

In October 2016, the company announced its insolvency (Hüsing, 2016). At the time of insolvency, the company employed 17 people (Hüfner, 2016). Later that year, the Swedish fintech company Klarna offered to hire all Cookies employees (Hüfner, 2016).

Krugljakow and Cheloufi knew each other from their past employer N26, a German direct bank. While Cheloufi worked in N26's product management team, Krugljakow managed N26's launch (L. Cheloufi, personal communication, August 15, 2019; G. Krugljakow, personal communication, August 15, 2019). With both founders working in management, functional diversity is low. Both founders hold a Master's degree in a business-related subject prior to founding Cookies. Thus, in terms of the field of education and level of education diversity can be considered low. The founders are about the same age and of the same gender, resulting in low gender and age diversity. An overview of the attributes of interest can be found in Table 6-3.

Table 6-3

*Venture team diversity – Cookies.*

| | Garry Krugljakow | Lamine Cheloufi | Diversity |
|---|---|---|---|
| Field of education | Business | Business | Low |
| Level of education | Master's | Master's | Low |
| Functional experience | Management | Management | Low |
| Gender | Male | Male | Low |
| Age at founding | 25 | 26 | Low |

With regards to shared experience, the Cookies founders worked for less than a year together at N26 (L. Cheloufi, personal communication, August 15, 2019; G. Krugljakow, personal communication, August 15, 2019). The company's failure is, according to a press release (Hüsing, 2016), a result of discrepancies between the founders: Cheloufi explained that he and his co-founder Krugljakow had professional and cultural differences and that Krugljakow used his shareholder rights to deliberately procrastinate a financing round. Notably, both founders had relevant industry experience through their work at N26. Additionally, Krugljakow spent more than three years working in banking before joining N26 (G. Krugljakow, personal communication, August 15, 2019).

### 6.2.4 Bullet

Bullet was founded in April 2018 in Berlin, Germany, by Leo Laun, Florian Eismann, and Seong-Min Kang (Hüsing, 2018). The company offered a service to businesses to digitize their postal mail. Customers had their mail sent to a post office in Munich, from where Bullet's logistics partner picked it up, opened it automatically and read it into Bullet's software (Schnor, 2018).

Bullet received a six-digit pre-seed investment in July 2018 from the VCF B10 and business angels (Hüsing, 2018). In April 2019 the company filed for insolvency, explaining that first, the market was not ready yet and second, that they were not able to receive additional funding from investors. The startup reported that it had 120 paying customers ("'Wir waren zu früh' - Postdigitalisierer Bullet gibt auf", 2019).

Laun and Eismann studied Business Administration and Kang has a Computer Science background (L. Laun, personal communication, August 15, 2019; F. Eismann, personal communication, August 15, 2019). All founders have a university degree: Kang and Laun both hold a Bachelor's degree and Eismann holds a Master's degree (S.-M. Kang, personal communication, August 15, 2019). Thus, the educational diversity is considered high. As for functional diversity, we find evidence for high diversity: Eismann held senior positions in online marketing and Kang held senior positions in software engineering. Before working on Bullet, Laun founded a startup called Digitalkasten, a service, similar to Bullet, but focused on private customers (Hüsing, 2018). With all founders being of the same gender, the gender diversity of Bullet's founding team can be considered low. The founders are 26, 33, and 36 years old, respectively, when founding the company and thus show high age diversity with regards to our sample. An overview of the attributes of interest can be found in Table 6-4.

Table 6-4

*Venture team diversity – Bullet.*

| | Leo Laun | Florian Eismann | Seong-Min Kang | Diversity |
|---|---|---|---|---|
| Field of education | Business | Business | Computer Science | High |
| Level of education | Bachelor’s | Master’s | Bachelor’s | High |
| Functional experience | Operations | Marketing | Technical | High |
| Gender | Male | Male | Male | Low |
| Age at founding | 26 | 33 | 36 | High |

Interestingly, Leo Laun already had significant industry experience prior to founding bullet, as Digitalkasten offered a similar service. Daniel Hoepfner, General Partner of B10, explained in a statement on LinkedIn that he would invest again in the team, as the team has complementary skills and is experienced (Hoepfner, 2019). Hoepfner (2019) saw the unwillingness to digitize of the German Mittelstand as a prime driver for the business' insolvency. Notably, Laun, Eismann and Kang had no shared work experience before founding Bullet (S.-M. Kang, personal communication, August 15, 2019; L. Laun, personal communication, August 15, 2019; F. Eismann, personal communication, August 15, 2019).

### 6.2.5 Lendstar

Lendstar was founded in 2013 by Jennifer Fizia and Christopher Kampshoff in Munich, Germany. The company offered a mobile app for transferring money between users (“Lendstar company information, funding & investors”, n.d.).

After a Pre-Seed round in 2013, the company secured Seed funding in 2015 led by VCF DvH Ventures, totalling 3 million Euros in equity funding (Wirminghaus, 2018; “Lendstar company information, funding & investors”, n.d.). Overall, the company’s app was downloaded more than 300,000 times (Wirminghaus, 2018). Nonetheless, CEO Kempshoff filed insolvency in August 2018 (Schlenk & Brücken, 2018). In a press release Kempshoff stated that despite of continuous growth the company was not able to maintain profitability (Schlenk & Brücken, 2018).

While Fizia graduated with a Master's degree in Journalism and Media Management, Kempshoff earned a Master's degree in Business Administration (J. Fizia, personal communication, August 15, 2019; C. Kampshoff, personal communication, August 15, 2019). Thus, we consider the team to have a low diversity in terms of the level of education and high diversity in terms of field of education. Before founding Lendstar, Kempshoff held senior positions in finance and Fizia spent several years working as a freelance copywriter and journalist (J. Fizia, personal communication, August 15, 2019; C. Kampshoff, personal communication, August 15, 2019). Hence, the team presents high functional diversity. As the founding team consists of one female and one male founder, gender diversity is high. With regards to age diversity, we found low heterogeneity in the founder's ages. An overview of the attributes of interest can be found in Table 6-5.

Table 6-5

*Venture team diversity – Lendstar.*

| | Jennifer Fizia | Christopher Kampshoff | Diversity |
|---|---|---|---|
| Field of education | Media & Communications | Business | High |
| Level of education | Master's | Master's | Low |
| Functional experience | Creative | Finance | High |
| Gender | Female | Male | High |
| Age at founding | 29 | 30 | Low |

### 6.2.6 Uberchord

In 2014, Uberchord was founded by Martin Polak, Eckart Burgwedel, and Simon Barkow-Oesterreicher in Berlin, Germany (Ksienrzyk, 2018). Uberchord was an interactive mobile app teaching its users how to play the guitar.

In March 2015, the company announced a 400,000 Euro Seed round (Richters, 2015). A Series A from VCF Passion Capital followed by the end of 2016 (Ksienrzyk, 2018), totalling 2.3 million Euros in equity funding. In an interview in May 2015, Burgwedel stated that the company reached close to a six-figure number in downloads. Uberchord filed insolvency in January 2019 stating that the firm was not able to secure additional funding from investors.

The team composition indicates high diversity with regards to the field of education. While Burgwedel studied Law, Polak, and Barkow-Oesterreicher studied Electrical Engineering and Computer Science, respectively (M. Polak, personal communication, August 15, 2019; E. Burgwedel, personal communication, August 15, 2019; S. Barkow-Oesterreicher, personal communication, August 15, 2019). All three founders graduated with a Master's degree from their university, indicating low diversity in terms of level of education. The team's functional experience can be considered high: before founding Uberchord, Burgwedel held a management position in a company he had founded. Polak worked for two years as a freelance software developer and Barkow-Oesterreicher worked as a computer scientist at the life science department of the ETH Zurich (Kasyap, 2016). The team's age diversity can be considered high: at the time Polak, Burgwedel, and Barkow-Oesterreicher founded the company they were 25, 39, and 37, respectively. Since all co-founders are male, gender diversity can be considered low. An overview of the attributes of interest can be found in Table 6-6.

Table 6-6

*Venture team diversity – Uberchord.*

| | Martin Polak | Eckart Burgwedel | Simon Barkow-Oesterreicher | Diversity |
|---|---|---|---|---|
| Field of education | Engineering | Law | Computer Science | High |
| Level of education | Master's | Master's | Master's | Low |
| Functional experience | Technical | Management | Technical | High |
| Gender | Male | Male | Male | Low |
| Age at founding | 25 | 39 | 37 | High |

### 6.2.7 Unruly

Unruly was founded in 2006 by Sarah Wood, Scott Button, and Matt Cooke in London, United Kingdom ("Unruly company information, funding & investors", n.d.). The company developed a video marketplace that connects advertisers with publishers.

There is little information on Unruly's financing prior to 2012. In January 2012 the company raised 25 million US-Dollars from VCFs Amadeus Capital and Endeit Capital ("Unruly company information, funding & investors", n.d.; Love, 2012). According to an article from TechCrunch, Unruly generated an annual revenue of approximately 50 million US-Dollars in 2014 (Lomas, 2015). In September 2015, global media conglomerate News Corp acquired Unruly for 176 million US-Dollars (Ghosh, 2017). Two years after the acquisition, the co-founders left the company (Ghosh, 2017).

We found evidence suggesting high educational diversity in the team – both in terms of field and level of education. While Wood earned a PhD in American Literature, Button graduated with a Master's degree in Philosophy. Cooke graduated from university with a Bachelor's degree in Computer Science. Similarly, the team's functional experience can be considered high (S. Wood, personal communication, August 15, 2019; S. Button, personal communication, August 15, 2019; M. Cooke, personal communication, August 15, 2019). Before founding Unruly, then-CEO Wood worked as a lecturer. Cooke held several positions in software development while Button founded Connextra, which he led to trade sale in 2005 (S. Button, personal communication, August 15, 2019). As the founding team consists of one female and two male founders, the team shows relatively high gender diversity. With regards to age diversity, we find low diversity in the founder's ages. An overview of the attributes of interest can be found in Table 6-7.

Table 6-7

*Venture team diversity – Unruly.*

| | Sarah Wood | Matthew Cooke | Scott Button | Diversity |
|---|---|---|---|---|
| Field of education | Language, Culture & History | Computer Science | Other (Philosophy) | High |
| Level of education | PhD | Bachelor's | Master's | High |
| Functional experience | Other (Lecturer) | Technical | Management | High |
| Gender | Female | Male | Male | High |
| Age at founding | 32 | 32 | 28 | Low |

Notably, Button gained industry experience before founding Unruly, as his previous company operated in the marketing field, too (S. Button, personal communication, August 15, 2019). Further, Button and Wood were already married to each other when they founded Unruly together (Ghosh, 2017).

## 6.3 Results

### 6.3.1 General Impact of Diversity

To assess the relationship of diversity in the founding team and success and failure in general, we examine the results of the first set of case studies, being Klarna, Spotify, Cookies and Bullet. Table 6-8 presents an abstraction of the company outcome and the general level of diversity.

While Klarna's and Cookies' founding teams show low diversity across all diversity attributes, Spotify's and Bullet's founding teams are diverse with regards to all attributes, except from gender diversity. As Table 6-8 highlights, we found no strong relationship between the level of general diversity and the company's outcome. Klarna represents a venture that is diverse across all attributes and highly successful from a VCF's perspective. Contrary, Cookies' diversity profile is similar to Klarna's, but the venture represents a failure from a VCF's perspective. Bullet's and Spotify's founding teams are diverse on most diversity attributes.

However, while Bullet represents a failure from a VCF's perspective, Spotify returned a multiple of the capital invested to its early investors.

Overall, we find that diversity in general is not a reliable predictor for a company's success or failure. An isolated view on a founding team's diversity can thus not be recommended. Other team-related factors, such as a team's shared experience, or a team's industry experience may influence the company's outcome, too. In the following discussion these will be further examined. Furthermore, we found that non-team-related factors, such as the market environment, product offering, and the company's timing impacts a company's probability to succeed, too.

Table 6-8

*General diversity and company outcome for the first set – overview.*

| | Low Diversity | High Diversity |
|---|---|---|
| Successful | Klarna | Spotify |
| Failed | Cookies | Bullet |

### 6.3.2 Impact of Age and Gender Diversity

The results of the statistical analysis in chapter 5 indicate that the configuration of a team's age and gender diversity impacts the company's outcome. Teams high in age diversity and low in gender diversity were found to be more successful than teams low in age diversity and high in gender diversity. Table 6-9 presents an overview of the company's outcome and the aforementioned configuration of age and gender diversity.

Spotify represents a successful venture that is high in age and low in gender diversity. Contrary, Uberchord's team failed while showing a similar disposition in terms of age and gender diversity. Lendstar represents a failed company that is low in age and high in gender diversity. However, ventures with a similar configuration of age and gender diversity and an opposite company outcome were found here, too: Unruly's founding team is low age diversity and high gender diversity, but presents, contrary to Lendstar, a successful investment for its investors.

Overall, the qualitative analysis shows that the combination of high age and low gender diversity as well as low age and high gender diversity cannot be generalized to be a reliable predictor of the company's success or failure.

Table 6-9

*Age and gender diversity and company outcome for the second set – overview.*

| | High Age and Low Gender Diversity | Low Age and High Gender Diversity |
|---|---|---|
| Successful | Spotify | Unruly |
| Failed | Uberchord | Lendstar |

# 7 Discussion

The objective of this thesis is to uncover the relationship between diversity in VC-backed venture teams and venture success and failure. The point of departure for this study was the gap in the literature between the research of the dynamics of organizational teams and of the success and failure of new ventures. We argue that the unique situation of a new venture, e.g., the peer-based team structure, high uncertainties in markets, and scarcity of resources, renders the direct application of findings of organizational team literature on new venture teams inappropriate. Instead, in this thesis, we followed an exploratory approach to the data and aimed to uncover measurable relationships between venture success and team diversity.

We begin this chapter with a discussion of our general findings from this study. We conclude that diversity is a complex notion that comprises partly contradicting effects. This finding argues for a more nuanced analysis of diversity. Following, we discuss the direct effects of the various diversity measures as a results from the static analysis, which are age diversity, field of education diversity, level of education diversity, functional diversity, and gender diversity. Furthermore, we discuss the results obtained from the qualitative analysis with regards to the influence of general diversity on a company's outcome as well as the relationship between age and gender diversity and a company's outcome. The qualitative analysis also shed light on possible predictors of venture outcome which lie beyond the scope of our quantitative analysis. In the context of previous research, these additional factors will be critically discussed in chapter 7.5. Representative for a general tendency in VC-backend ventures, our sample shows a distinct imbalance towards young male co-founders. We discuss these phenomena and suggest reasons and meaningful points of departure for further research.

## 7.1 Discussion of the General Findings

The quantitative analysis proves a direct and significant impact of team diversity on the success and failure of new ventures. However, this influence is not persistently one-sided, neither towards success nor failure but shows opposing effects. As the results from the quantitative and qualitative analysis show, the distinction between different diversity measures is crucial. This is in line with a meta-analysis of 24 studies assessing the relationship between team diversity and performance (Webber & Donahue, 2001). Over the 24 studies, the researchers found no consistent relationship between types of diversity and group performance. In the following, we will discuss the results for the various diversity measures and compare our findings with the literature.

Our results indicate that age diversity has a positive impact on venture success in general. Notably, models 1 and 4 in the logistic regression yielded no significant value for age diversity. Models 2, 3, 5, and 6 in the logistic regression revealed that age diversity is significant on a 91.7% to 92.9%-level. The hazard analysis yielded consistent significant values for age diversity on a 97.6% to 98.2%-level and thereby confirms the significant positive impact of age diversity on venture success.

## 7.2 Discussion of the Direct Effect of the Diversity Measures

### 7.2.1 Age Diversity

Our result regarding age diversity is in line with the findings from Murray (1989) who states that age diversity is positively related to team performance. Other researchers too attribute a positive impact on age diversity and claim that age diversity impacts the turnover positively (Tsui & O'Reilly, 1989; Jackson et al., 1991; Wiersema & Bird, 1995). Interestingly, the findings from other research appear to contradict these findings on first sight. Ireland et al. (1987) argue that individuals of similar age are shaped by similar experiences in life and thus share similar beliefs and values. More, Pfeffer (1983) claims that people that share the same age share similar values and perspectives, and age is also found to be a strong predictor of a close friendship (Verbruggee, 1977). What appears to be arguments against a positive impact of diversity in age on first sight, it seems that the similar values, perspectives, and beliefs are detrimental for venture success. Instead, a broader spectrum of experiences and perspectives that go along with different ages seem to be beneficial.

Overall, the results from empirical studies on the relationship between age diversity and (entrepreneurial) team performance are mixed. Foo (2011) shows a positive relationship while three other studies reveal a negative relationship with team effectiveness (Foo, Wong, & Ong, 2005), team stability (Hellerstedt, Aldrich, & Wiklund, 2007), and growth (Amason, Shrader, & Tompson, 2006). Other studies show no significant relationship. Notably, the samples for each study from which the results are derived differ significantly in most studies examining this relationship. For example, Foo (2011) and Foo, Wong, and Ong (2005) rely on business plan competitions with university students, while Hellerstedt, Aldrich, and Wiklund (2007) base their sample on all individuals who enter into self-employment in knowledge-intensive industries in Sweden from 1996 to 2000, and Amason, Shrader, and Tompson (2006) relate their study to top-level management teams. Other, in this thesis, we gathered data from existing ventures all of which are VC investment candidates. Therefore, we propose that our statistically significant finding across different models – that age diversity has a positive impact on venture success – is most pertinent for venture capital researchers and practitioners.

### 7.2.2 Field of Education Diversity

According to our analysis, the diversity in the fields of education of a team has no impact on the success of a new venture. Although the hazard analysis reports some significance ($0.072 < p < 0.075$) in models 1 to 3, the logistic regression does not confirm this result and reports no significance across all models ($0.206 < p < 0.766$). The disagreement between the two models points to some uncertainty and prohibits generalization.

Previous research regarding the relationship between the field of educational diversity and venture financing has yielded mixed results (Foo et al., 2005; Zimmerman, 2008). While two studies discovered a positive impact on team variability (Foo, Sin, & Yiong, 2006) and new venture sales growth (Amason, Shrader, & Tompson, 2006), two other studies showed a negative relationship between the field of education diversity and team stability (Hellerstedt, Aldrich, & Wiklund, 2007) and new venture revenues (Ensley, Hmieleski, & Pearce 2006). Other empirical studies showed no association of field of education diversity and team innovativeness (Henneke & Lüthje 2007), external assessment of a business idea (Foo, Wong,

& Ong 2005), market performance and profitability (Amason, Shrader, & Tompson, 2006), or member satisfaction (Foo, Sin, & Yiong, 2006). Jehn (1997) reports that educational diversity increases task-related conflict (as opposed to personal conflict) which positively impacts team performance. Also, Zimmerman (2008) states that a heterogeneous mix of educational backgrounds in a team enriches the overall range of perspectives and creativity.

Acknowledging the inconclusive findings in both our analysis and previous studies, we assume that field of education diversity does not have a significant impact on venture success. However, to eliminate uncertainties and to conclude on this issue, further research is needed.

### 7.2.3 Level of Education Diversity

Similarly, the relationship between venture success and the level of education diversity is also inconsistent. Two studies found a positive relationship between level of education diversity and external assessment (Foo, Wong, & Ong, 2005) and sales growth (Amason, Shrader, & Tompson, 2006). Conversely, another study showed the opposite impact on sales growth (Ensley, Carland, & Carland, 1998). Supporting the hypothesis that educational diversity has no impact on venture success, we found the level of education to have no significant impact on team performance.

### 7.2.4 Functional Diversity

Also, our results show no consistent significance for functional diversity. In the logistic regression, no model shows any significance. Interestingly, in the hazard analysis, models 1 and 4 report a rather high significance on a 98.1% and 97.4% level, respectively. Both models 1 and 4 share the same success/failure definition which is “has exit”. Considering this, the results could indicate that functional diversity has a negative influence on survival until the exit of a venture but not on a general stage progression. However, considering the mostly non-significant results, we cannot generalize this finding. Again, more research is needed to verify this hypothesis.

Previous research on diversity attributes functional experience a positive force towards increased team performance, creativity, and innovation (Milliken, Bartel, & Kurtzberg, 2003; Bantel & Jackson, 1989; Dearborn & Simon, 1958; Hambrick & Mason, 1984). However, an increase in functional diversity is also correlated with an increase in interpersonal conflict which is found to have negative effects on team performance (Amason, 1996).

The results from empirical studies are, again, inconclusive. Four empirical studies attribute functional diversity a positive influence on team performance (Beckman, Burton, & O'Reilly, 2007; Aspelund, Berg-Utby, & Skjevdal, 2005; Ucbasaran et al., 2003; Davis, Aldrich, & Longest, 2009), two other studies demonstrated that functional diversity is negatively correlated with new venture revenues (Ensley, Carland, & Carland, 1998), team stability, and firm survival (Goethner & Stuetzer, 2009). Another five studies show no significant effects on team effectiveness, new venture profitability, sales growth, and market performance (Chowdhury, 2005; Foo, 2011; Amason, Shrader, & Tompson 2006; Chandler & Lyon, 2001; Ensley, Carland, & Carland, 1998).

With the mixed results from our analysis, we can only affirm the inconclusive findings shown in the literature and thereby illustrate the importance of future research on this particular measure. Both, more quantitative studies verifying or falsifying the significance of functional diversity and qualitative studies examining the inner workings of this phenomenon are needed to conclude on its effect on venture success.

### 7.2.5 Gender Diversity

Finally, we found gender diversity to have a generally negative effect on new venture success, although the models with success/failure definition 1 ("has exit") did not yield significant results. For the other models, the significance ranges between 92.8% and 94% in the logistic regression and between 91.6% and 93.6% in the hazard analysis. The effect size of gender diversity varies in the logistic regression and in the hazard analysis but all models show the same effect direction which negatively correlates with venture success.

The certainty of this finding suffers from the imbalance of the dataset: Less than 17% of all companies included one or more women and only 6% of all founders are female in our sample. In the literature, the effect of gender diversity on team performance is found to be mixed. Foo et al. (2005) argue that gender diversity might decrease effective communication within the team and lead to lower cohesiveness. Then again, mixed teams might be more apt to resolve emotional conflict thanks to higher social sensitivity that is positively correlated with the number of females on a team (Wolley et al., 2010). Our results suggest that the increased conflict induced by a higher gender diversity outweighs the positive effects.

The literature regarding the direct effect of gender diversity on team and venture success is inconclusive. Out of four empirical studies assessing the influence of gender diversity on entrepreneurial performance, one study showed a positive relationship (Hellerstedt, Aldrich, & Wiklund, 2007), one study showed a negative correlation with team productivity (Davis, Aldrich, & Longest, 2009), and another two displayed non-significant results. We believe that our results are most relevant to VCFs because of our narrow focus on VC-backed companies (in Europe) in contrast to other studies. More research on this particular matter is needed to attain certainty. Possibly, the impact of gender diversity has different consequences in the various stages of the venture life cycle. The starting point for further research could be an examination of the direct effects of gender diversity per stage. Also, an investigation of the differences between dominantly male and dominantly female ventures, although scarce, might reveal novel insights.

## 7.3 Discussion of the General Impact of Diversity

As highlighted in chapters 2 and 3, previous literature presents mixed evidence in terms of the impact of diversity on a venture's performance – both on team- and firm-level. Despite the ambiguity of these results, researchers found evidence that VCFs favour diverse teams in their decision-making process (e.g., Dixon, 1991; Goslin & Barge, 1986; Eisele et al., 2004; Vogel et al., 2014).

Goslin and Barge (1986) found that VCFs value complementary skills and Dixon (1991) claims that VCFs prefer educational and functional diversity over teams where all members have a similar background. Furthermore, Vogel et al. (2014) found that a founding team's educational, functional experience, age, and gender diversity have a positive and significant influence on the willingness of investors to supply capital. In fact, Eisele et al. (2004) found that a team's heterogeneity ranks among the most important criteria in a VCFs decision-making process.

Our results suggest that diversity drew this special attention wrongfully. In the qualitative analysis, we found no evidence supporting a VCFs tendency to favour overall diverse venture teams. Particularly, Klarna illustrated that a company can succeed despite low levels of diversity in all here observed attributes. Subsequently, high general diversity cannot be considered a necessity for success. Bullet's founding team is highly diverse with regards to all attributes, except from gender. However, the company failed already in the very early stage before raising a Seed round.

Taken together, we found that diversity as a whole cannot be generalized as success promoting or inhibiting. Therefore, VCFs should pay less attention to general diversity in their decision-making process and instead apply a more granular assessment of diversity in teams.

## 7.4 Discussion of the Impact of Age and Gender Diversity

The quantitative analysis revealed that both age and gender diversity have a significant impact on the success of a venture, however in opposite directions. We found that increased age diversity in the founding team is a predictor for success whereas increased gender diversity seems to negatively impact the venture's probability of success.

Based on this solely quantitative finding, we hypothesized that a combination of high age diversity and low gender diversity is a predictor for certain success and, in turn, a combination of low age diversity and high gender diversity is a predictor for certain failure. In the qualitative study, two case companies suggest this hypothesis holds true: Spotify's successful team is high in age diversity and low in gender diversity and Lendstar represents a failed venture that is low in age diversity and high in gender diversity as the hypothesis would predict. However, two other cases falsify the ubiquitous correctness of the hypothesis: Unruly is a successful venture that shows low age diversity and high gender diversity in the founding team and Uberchord has the same combination of high age and low gender diversity as Spotify but failed.

The results of the qualitative analysis indicate that singular diversity factors, although significant, cannot simply be added and extrapolated to all ventures. Still, as the quantitative analysis proves, age and gender diversity are reliable predictors for venture success and failure. However, in the VC decision-making process, these factors must not be interpreted as isolated guarantees but only part of the puzzle.

## 7.5 Discussion of Other Predictors for Venture Success

In this thesis we apply an abductive research approach to challenge the generated insights in a multi-level analysis process. Following, we discuss unanticipated findings of the qualitative analysis which may provide guidance for future research of team diversity.

The results of the qualitative analysis indicate no strong relationship between industry experience and venture outcome. Out of the three successful startups, we found that in two, namely Spotify and Klarna, no co-founder had industry experience, and that only Unruly's co-founder Scott Button has had previous industry experience. Among the four failed ventures, we found equal support for a positive impact of the presence and absence of industry experience, suggesting that industry experience does not influence company outcome significantly.

This is an important finding because most VCFs value the presence of industry experience in venture teams (MacMillan et al., 1985; Shrader et al., 1997). Across previous research, there is consensus that industry experience within the founding team is a dominant selection criterion in the VC decision-making process (MacMillan et al., 1985; Muzyka et al., 1996; Eisele et al., 2004; Franke et al., 2008). Contrary, our results suggest that industry experience should not play a dominant role in the decision-making process of VCFs. Our results also match those observed in an earlier study. Streletzki and Schulte (2013A) found industry experience not to be a dominant factor in terms of exit performance.

Another notable finding is that shared experience in the form of prior joint work experience and friendship was found to be more prevalent in successful startups than in failed ones. As highlighted above, the founders of Klarna shared a number of experiences, ranging from a joint work experience at Burger King to a joint education experience at the Stockholm School of Economics. Similarly, Spotify's founders Ek and Lorentzon were befriended prior to undertaking their venture, and also two of the Unruly founders have a strong bond since they were married to each other before founding their company. Conversely, similar strong ties could not be observed in the failed companies Bullet, Lendstar, and Uberchord. The only exception among the failed companies presents Cookies: Krugljakow and Cheloufi worked together at N26 before they founded Cookies together.

However, these results must be interpreted with caution. Information on failed ventures is generally more scarce than on successful ventures – naturally, highly successful companies such as Spotify and Klarna draw attention from the media. Thus, our findings based on the available data may be biased. Nonetheless, future research should investigate the impact of shared experience within founding teams on venture success and failure. With regards to the role of friendship, research from D'hont, Doern, and García (2015) provides an indication of a positive impact of friendship on entrepreneurial processes. However, much remains to be understood of the role and types of friendship in the context of the success and failure of ventures. As for the effect of joint work experience on venture outcome, previous research supports our finding. Beckman et al. (2006) found that joint work experience positively impacts the chance of going public (IPO), and also Streletzki and Schulte (2013A) state that the presence of prior joint work experience in venture teams has a positive influence on VC exit performance. Despite the limited generalizability of our findings, we recommend future studies on the relationship between shared experience and venture outcome.

## 7.6 Discussion of the Gender Imbalance

The huge gap between male and female entrepreneurs is concerning as it suggests a systematic discrimination towards women. The imbalance in our dataset is representative for startups in general. A recent study shows that female-led startups only receive 10% of all venture capital investment (Truss et al., 2019). This makes it seem likely that women are overlooked in the investment process. However, as the report states, one problem is rather that only 5% of all ventures seeking investment are female-led – out of which the majority (4% of the total) received investment. Thus, the problem is not a systematic discrimination by decision-makers but a general imbalance of male and female finance seekers. Although our results indicate a negative relationship of gender diversity, this must not be generalized following the faulty rationale that the more women in a founding team the worse a venture performs. On the contrary, research suggests that teams dominated by females outperform other teams (Wolley et al., 2010). The root cause for this bias and its implications for both, diversity research and venture capital investment practice, are highly important but deep and obscure. The analysis of this phenomenon cannot be investigated in more depth in this thesis but presents a topic for further research. A potential point of departure is the gender-biased assessment of risk: Research shows that women are more reluctant to take risks, which is a fundamental part of every entrepreneurial endeavour (Morrongiello & Dawber, 2000; Mather & Lighthall, 2012). Partly caused by biological factors but often also reinforced by parents and peers, the gender-specific conception of risk might be one of many interrelated factors causing this imbalance. More recent research from Kanzle et al. (2018) suggests that the gender imbalance in startup funding is a result of a gender bias in the questions that VCFs ask startup teams. The field study demonstrates that investors tend to ask male teams promotion-focused questions while female teams are being asked prevention-focused questions, with matching responses. Kanzle et al. (2018) conclude that divergent funding outcomes are a result of the type of questions asked by investors.

## 7.7 Discussion of the Dominantly Young Age of Founders

According to our sample, the age at which an entrepreneur established her or his company is 30.29. With an average of 8.37 years to exit, the successful entrepreneur is just under 39 years old. These findings are in line with findings from other research. The average age of founders who won TechCrunch awards, which are generally targeted at promising early-stage ventures, is 31 at the time of foundation (Azoulay, Jones, Kim, & Miranda, 2018). Similarly, the age of founders who were nominated to lead the fast-growing startups in 2015 by inc. magazine was 29 (Azoulay et al. 2018). However, a recent study suggests that the most successful founders are not young but middle-aged (Azoulay et al., 2018). The researchers found that the average age of a founder of the top 0.1% of ventures (based on growth in their first five years) is 45 years when they started their company. Supposing this finding and the findings from our sample are generalizable, it is unclear where the bias towards young founders originates from. Azoulay et al. (2018) offer two explanations: First, investment decision-makers might hold the flawed belief that youth is a crucial factor for success. Second, venture capitalists aim not to identify the ventures with the highest potential growth but the highest potential return on investment. Since young founders are generally more financially-constrained and more dependent on external investment than older founders, young founders present a better "deal" to a venture capitalist (more equity for less money). Still, the research on age in the context of venture capital-intensive companies needs both, more proof and more explanations. Again, this topic lies beyond the scope of this thesis but presents a topic for further research.

## 7.8 Discussion of the Inconclusiveness in Diversity Research

The assessment of the various diversity measures reveals that our findings are generally in line with previous research. Problematically, as we have discussed, the literature itself is inconsistent with its findings on the relationship between diversity and team success. We present the following three explanations for the inconclusiveness.

First, various studies apply different definitions of diversity. In this study, we followed the notion of diversity proposed by Harrison and Klein (2007), while other studies confuse various measures which prohibits the comparability across studies. A universal agreement in the diversity research that could start by defining fundamental diversity categories, such as demographic, functional, and psychological diversity would allow consistency and comparability.

Second, the definitions of success and failure in the literature are far from concurrent. Owing to the various settings in which diversity in teams is measured, these definitions differ greatly. Some studies allow success to be specified by peers, some take revenue or growth as their basis and we found ourselves defining another measure that respects the circumstances of VC-backed ventures that includes both successes and failures. With this broad spectrum of delimitations, inconsistent findings are only consequential.

Third, we found the respective samples underlying the different studies to be hardly comparable. Some studies base their analysis on hypothetical situations envisioned by university students and others include every means of self-employment, be it the new restaurant, hairdresser or high-growth startup with hundreds of employees and global operations. As far as we know, this thesis is the first piece of research that bases its analysis of diversity on a large body of successful and unsuccessful VC-backed companies and its founders in Europe.

## 7.9 Theoretical and Practical Implications

With the extensive examination of the functioning of diversity against the background of venture financing in this thesis, we contribute to a deeper understanding of the impact of diversity in new venture teams. Based on a large dataset of founders and their ventures we derived quantifiable findings that are most relevant for diversity researchers and venture financing practitioners alike. With certainty, we can conclude that age diversity has a positive impact on venture success.

The concept of diversity is not a trivial phenomenon. Researchers have to admit that diversity as a whole measure cannot hold a universal statement. As this thesis proves again, neither is diversity fundamentally good nor bad. One must be specific in the distinction of the different diversity measures, such as gender, age or functional diversity and one must also be attentive to the context of diversity. Even the seemingly slight difference between, e.g., a team that engages in creative and innovative thinking and a team that focuses on the operational implementation of an idea, will alter the impact of diversity. To gain relevant insights, researchers and practitioners alike must be careful generalizing findings from research that might not apply to their specific context.

With the large body of research on diversity that points in various directions, one might succumb to cherry-picking the one result that conveniently fits one's argument. Acknowledging this, caution is advised, both for researchers and practitioners to not fall for seemingly factual conclusions.

Finally, the partly opposing findings from the various studies do not permit negligence of diversity as a whole but rather argue for more nuanced research on this context-dependent measure.

## 7.10 Limitations and Further Research

The basis for the analysis in this thesis is a self-created dataset that serves a sample. Generally, any study of such kind entails several interpretative elements which induce limitations to the overall robustness of the results and conclusions.

Regarding this study, the first limitation is related to the data sources. We relied on publicly available data that we were unable to attest universal correctness. We deliberately chose our sources based on two main criteria, namely availability and reliability. Especially the reliability of the sources is questionable in some regards. Concerning Crunchbase, one of the two main websites we used to source relevant ventures, we were not able to holistically comprehend the data mining process. Without full transparency, we have to assume that relevant information is omitted or false. However, as popular media outlets, such as TechCrunch (Glasner, 2018) and Forbes (Columbus, 2019) rely on this source, we can be reasonably sure of its accuracy. Next, LinkedIn, our second data source relies primarily on self-reported data from their members. The information stated on a LinkedIn profile are generally not confirmed by any instance. Thus, the reliability of the data is impaired. Although other sources exist that feature information regardings founders, such as AngelList ("About AngelList", n.d.) or Xing ("About Xing", n.d.), no other source matches the extent of information LinkedIn offers.

The second limitation that this thesis is exposed to is the subjective interpretation of some attributes of interest. Especially the abstraction from the professional experience that is listed on a founder's LinkedIn profile to the dominant experience that is then grouped into broader groups requires some interpretation from the researchers. Similarly, the definition of overarching groups of functional experiences and fields of education follow no thoroughly tested framework but resulted from an intuitive argumentation and adaptation from other guidelines, such as the distinction of fields of education which universities have in place. Acknowledging this second limitation, we decided not to include three potentially meaningful variables that concern the previous exposure of founders to startups in general, the foundation of a venture, and the industry the venture operates in. Generally, the subjective freedom the researchers have to handle suggests that other researchers with the same aim would present different results. This, of course, impairs the credibility of this study.

Third, the manual data collection process imposes a limitation in the scope of data that we could collect. We sourced the personal information of just under 500 founders which is arguably a large dataset. However, the information of each founder is primarily used to derive the diversity indices for the 178 companies in our dataset. Additionally, missing values prohibit the calculation of every diversity measure for every venture. This results in even less relevant cases. As we have described previously, the number of cases included in the analysis falls as low as 89, which is only half of all ventures. With the reduced number of observations, the reliability of the results derived by the static models is compromised.

The fourth limitation refers to our analysis and the handling of control variables and moderating effects. In the logistic regression we have included two control variables, namely the year of foundation as a categorical value and number of co-founders a venture has. Due to technicalities, the year of foundation was not included in the hazard analysis but only the number of co-founders. That reduces the comparability of both models to some degree. We argue, that the primary objective of the hazard analysis is to call into question the results of the logistic regression. As such, it serves an addition to the logistic regression. Furthermore, the consideration of more control variables and their mediating effects could further improve the reliability of the results.

Future research on the topic of diversity in the context of VC-backed ventures should take these limitations into conderistraion in the design of their study. As we have discussed earlier virtually every result from this study on the background of the extant literature calls for more research. With the varying examination of contexts and definitions of diversity, the literature is inconclusive. Our suggestion for further research is to focus on a specific context, e.g., VC-backed ventures in Europe, instead of trying to derive a universal formula to explain diversity. As this thesis has proven, diversity is a multifaceted concept that requires and deserves more nuance.

# 8 Conclusion

To recapture, in this thesis we analyzed and quantified the impact of diversity in founding teams on venture success and failure with the aim to both advance the diversity research and to improve the VC-decision-making process. After an introduction in chapter 1 in which we illustrated the importance of a more VC-oriented study, we identified crucial gaps in the literature in chapter 2. In chapter 3 we lay the theoretical foundation in which we described the functioning of venture financing and the inner workings of diversity. In the following chapter 4, we described our research methodology and argued for an abductive approach that favours a more exploratively engagement with the data. The quantitative analysis in chapter 5 is based on 495 founders in 178 VC-backed companies – including both failed and successful cases. Applying two different means of statistic analysis, namely binomial logistic regression and hazard analysis, we calculated the direct effects of various diversity indices across multiple models with varying dependent and independent variables which allow us to derive robust results. Following, we scrutinized the quantitative results with a qualitative examination of a number of representative cases. In the subsequent chapter 7, we discussed the findings from both the quantitative and qualitative analysis before we concluded on the thesis in chapter 8.

In summary, the results of this thesis prove that also for VC-backed ventures the effects of diversity are not trivial. In line with extant literature, we found that diversity does not have a unidirectional effect, neither positive nor negative. Instead, the consideration of the specific measure is crucial. Our analysis shows that neither diversity in functional experience, diversity in the level of education nor the diversity in the field of education has a significant influence on the success or failure of a VC-backend venture. Further, we can derive from the analysis that increased gender diversity has a negative impact and age diversity has a positive impact on the success of a venture.

We are confident that these results are highly relevant for the improvement of the VC decision-making process through quantification to steer away from biases and ill-informed decisions based on gut feelings. Quantified team diversity indicators present a promising data source, especially in the validation of an early-stage venture when data is scarce. However, caution is advised when concluding on the effects of diversity. Diversity is a complex topic that does not allow a generalization across different measures and contexts.

The advancement of diversity research in the context of VC is of utmost importance. VC-backed ventures have become an essential driver of the economy by stimulating innovation and employment. Uncovering the dynamics of diversity in founding teams would help both, founders in the configuration of their team and VCFs in their decision-making to ultimately foster economic growth.

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# Appendix

## A: Google Sheets App Script for the Calculation of Diversity Indices

```
var cols = {
  co: 0,
  age: 4,
  gender: 6,
  func: 8,
  edu: 12,
  edu_level_ord: 15,
  edu_level_nom: 16,
}

function standardDeviation(values){
  var avg = average(values);

  var squareDiffs = values.map(function(value){
    var diff = value - avg;
    var sqrDiff = diff * diff;
    return sqrDiff;
  });

  var avgSquareDiff = average(squareDiffs);

  var stdDev = Math.sqrt(avgSquareDiff);
  return stdDev;
}

function average(data){
  var sum = data.reduce(function(sum, value){
    return sum + value;
  }, 0);

  var avg = sum / data.length;
  return avg;
}

function getFoundersByCompany(company) {
```

```
  const sheet = SpreadsheetApp.getActive().getSheetByName('Founders');
  const rows = sheet.getDataRange().getValues();
  return rows.filter(function(row) { return row[cols.co] === company });
}

function getExperiences(arr) {
  const experiences = [];
  arr.forEach(function(row) {
    experiences.push(row[cols.func]);
  });

  return experiences;
}

function getValues(arr, type) {
  return arr
  .map(function(row) { return row[cols[type]] })
  .filter(function(i) { return i.length > 0 });
}

function getGenders(arr) {
  return arr.map(function(row) { return row[cols.gender] });
}

function getAges(arr) {
  return arr.map(function(row) { return row[cols.age] });
}

function calcSimpsonIndex(arr) {
  if (arr.length === 0) return "";

  const uniques = {};
  arr.forEach(function(xp) {
    uniques[xp] = uniques[xp] ? uniques[xp] + 1 : 1;
  });

  const Simps = Object.keys(uniques).map(function(key) {
    const pi = uniques[key] / arr.length;
    return pi * pi;
  });

  const S = Simps.reduce(function(acc, current) {
    return acc += current;
  });
```

```
  return S;
}

function calcShannonIndex(arr) {
  if (arr.length === 0) return "";

  const uniques = {};
  arr.forEach(function(xp) {
    uniques[xp] = uniques[xp] ? uniques[xp] + 1 : 1;
  });

  const Hs = Object.keys(uniques).map(function(key) {
    const pi = uniques[key] / arr.length;
    return pi * Math.log(pi);
  });

  const H = Hs.reduce(function(acc, current) {
    return acc += current;
  });

  return -H;
}

function calcFunctionalDiversity(company, index) {
  const founders = getFoundersByCompany(company);
  const xps = getExperiences(founders);
  const fd = calcShannonIndex(xps);

  return fd;
}

function calcGenderDiversity(company, index) {
  const founders = getFoundersByCompany(company);
  const genders = getGenders(founders);
  const gd = calcShannonIndex(genders);

  return gd;
}

function calcDiversity(company, type, index) {
  const founders = getFoundersByCompany(company);
  const values = getValues(founders, type);
```

```
  var score;
  if (index === "simpson") {
    score = calcSimpsonIndex(values);
  } else {
    score = calcShannonIndex(values);
  }

  return score;
}

function calcAgeDiversity(company) {
  const founders = getFoundersByCompany(company);
  const ages = getAges(founders).filter(function(age) { return age > 0 });
  const stdDev = ages.length > 1 ? standardDeviation(ages) : "";
  return stdDev;
}

function calcAgeAverage(company) {
  const founders = getFoundersByCompany(company);
  const ages = getAges(founders).filter(function(age) { return age > 0 });
  const avg = ages.length > 0 ? average(ages) : "";
  return avg;
}
```

## B: Google Sheets App Script for the Calculation of Success and Failure

```
function getCo(company) {
  const sheet = SpreadsheetApp.getActive().getSheetByName('Companies');
  const rows = sheet.getDataRange().getValues();
  const co = rows.filter(function(row) { return row[0] === company })[0];

  return {
    round: co[8],
    isOperating: co[11] === "Yes" ? true : co[11] === "No" ? false : "",
    exit: co[15],
    hasExit: co[15] === "Yes" ? true : co[15] === "No" ? false : "",
    raised: co[6],
    employees: co[10],
  }
}

function calcSuccess1(company) {
  const co = getCo(company);

  var success;
  if (co.hasExit) {
    success = 1;
  } else if (!co.isOperating && !co.hasExit) {
    success = 0;
  }

  return success;
}

function calcSuccess2(company) {
  const co = getCo(company);

  var success;
  if (co.hasExit || (co.round > 2 && co.isOperating)) {
    success = 1;
  } else if (!co.isOperating && !co.hasExit) {
    success = 0;
  }

  return success;
```

```
}

function calcSuccess3(company) {
  const co = getCo(company);

  var success;
  if (co.hasExit || ((co.raised >= 10 || co.employees >= 50) &&
co.isOperating)) {
    success = 1;
  } else if (!co.isOperating && !co.hasExit) {
    success = 0;
  }

  return success;
}
```

## C: Role Categorization Guide

**Marketing:** Brand Manager, Marketing Manager, CMO, Marketing Director, Marketing Executive, Product Marketing, Engagement Director

**Technical:** Developer, Programmer, CTO, Software Architect, SysAdmin, Application Engineer, Engineer, Game Developer, Technical Architecture, Web Development, Systems Architect, Data Analyst, AI

**Management:** General Manager, CEO, VP Strategy, Managing Partner, Business Strategist, Project Manager, Product Manager, Product Lead, IT Manager, Technical Manager

**Operations:** Sales, COO, Account Management, Business Development, Operations Manager, Customer Support

**Finance:** Manager Finance, Tax Director, Trader, Financial Analyst, Investment Manager, PE, Investment Banker, Portfolio Analyst

**Consulting**: Consulting, Management Consultant, Associate

**Creative:** Art Director, Creative Director, Interface Designer, Game Artist, UI/UX, Head of Design

**Other:** Legal, Researcher, HR, Law, MD, Composer, Musician, Journalism, Columnist, Fashion

# D: Multicollinearity Tables

Table D-1

*Multicollinearity table for Shannon-Wiener indices.*

| | Age diversity | Gender diversity | Functional diversity | Field of education diversity | Level of education diversity | Number of co-founders |
|---|---|---|---|---|---|---|
| Age diversity | -- | 1.174 | 1.082 | 1.174 | 1.170 | 1.164 |
| Gender diversity | 1.062 | -- | 1.062 | 1.008 | 1.062 | 1.061 |
| Functional diversity | 1.274 | 1.382 | -- | 1.337 | 1.374 | 1.279 |
| Field of education diversity | 1.306 | 1.241 | 1.265 | -- | 1.287 | 1.223 |
| Level of education diversity | 1.088 | 1.092 | 1.086 | 1.076 | -- | 1.079 |
| Number of co-founders | 1.322 | 1.333 | 1.235 | 1.248 | 1.319 | -- |

Table D-2

*Multicollinearity table for Simpson indices.*

| | Age diversity | Gender diversity | Functional diversity | Field of education diversity | Level of education diversity | Number of co-founders |
|---|---|---|---|---|---|---|
| Age diversity | -- | 1.172 | 1.081 | 1.172 | 1.167 | 1.153 |
| Gender diversity | 1.048 | -- | 1.048 | 1.005 | 1.047 | 1.047 |
| Functional diversity | 1.183 | 1.283 | -- | 1.246 | 1.276 | 1.224 |
| Field of education diversity | 1.207 | 1.158 | 1.173 | -- | 1.199 | 1.148 |
| Level of education diversity | 1.058 | 1.061 | 1.057 | 1.055 | -- | 1.051 |
| Number of co-founders | 1.213 | 1.233 | 1.177 | 1.173 | 1.220 | -- |

# E: Python Code for the Application of the Cox Proportional-Hazards Model

```
# Install and import modules
!pip install -q lifelines

from lifelines import KaplanMeierFitter
from lifelines import CoxPHFitter
import pandas as pd
import numpy as np
import csv
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline

pd.options.display.max_rows = 10
pd.options.display.float_format = '{:.2f}'.format

# Read file
df = pd.read_csv("mt-dataset-v3.csv", sep=",")

# Invert success
df['failure1'] = df['success1'].replace({0:1, 1:0})
df['failure2'] = df['success2'].replace({0:1, 1:0})
df['failure3'] = df['success3'].replace({0:1, 1:0})

# Define failure descriptor (iterate)
fail_desc = "failure1"

# Construct arrays
shannon_arr = [fail_desc, 'Count cofounders', 'Series', 'Age Diversity (St
Dev)', 'Gender Diversity (Shannon)', 'Functional Diversity (Shannon)',
'Educational Diversity (Shannon)', 'Education Level Diversity (Shannon)']
simpson_arr = [fail_desc, 'Count cofounders', 'Series', 'Age Diversity (St
Dev)', 'Gender Diversity (Simpson)', 'Functional Diversity (Simpson)',
'Educational Diversity (Simpson)', 'Education Level Diversity (Simpson)']

# Drop null values
df_shan = df.loc[:,shannon_arr]
df_shan = df_shan.dropna()

df_simp = df.loc[:,simpson_arr]
```

```
df_simp = df_simp.dropna()

# Construct Kaplan-Meier estimate based on Series and the failure description.
durations = df_shan["Series"].tolist()
event_observed = df_shan[fail_desc].tolist()

## Create a kmf object
kmf = KaplanMeierFitter()

## Fit the data into the model
kmf.fit(durations, event_observed, label='Kaplan Meier Estimate')

## Create an estimate
kmf.plot(ci_show=False)

# Create Cox model (iterate dataframe)
## Instantiate class
cph_shan = CoxPHFitter()

## Fit the data to train the model
cph_shan.fit(df_shan, 'Series', event_col=fail_desc)

## Print summary
cph_shan.print_summary(decimals=3)

## Visualize
cph_shan.plot()

## Check assumptions
df_shan.check_assumptions(df_shan, p_value_threshold=0.05, show_plots=True)

## Calculate residuals and plot result
r_dev = df_shan.compute_residuals(df_simp, 'deviance')
r_dev.plot.scatter(
    x='Series', y='deviance', c=np.where(r_dev[fail_desc], '#008fd5',
'#fc4f30'),
    alpha=0.75
)

r_mart = cph_shan.compute_residuals(df_shan, 'martingale')
r_mart.plot.scatter(
    x='Series', y='martingale', c=np.where(r_mart[fail_desc], '#008fd5',
'#fc4f30'),
    alpha=0.75
```

```
)

## Predict survival
cph_shan.predict_survival_function(tr_rows).plot()
ix = tr_rows.index.tolist()
df.iloc[ix, 0]
```

# F: Diversity Averages

Table F

*Averages for all diversity indices.*

| | Mean | St. Dev. | Min. | Max. |
|---|---|---|---|---|
| Age Diversity (St Dev) | 2.420 | 2.521 | 0.000 | 11.813 |
| Gender Diversity (Shannon) | 0.101 | 0.235 | 0.000 | 0.693 |
| Gender Diversity (Simpson) | 0.929 | 0.166 | 0.500 | 1.000 |
| Functional Diversity (Shannon) | 0.597 | 0.424 | 0.000 | 1.386 |
| Functional Diversity (Simpson) | 0.609 | 0.261 | 0.250 | 1.000 |
| Educational Diversity (Shannon) | 0.423 | 0.403 | 0.000 | 1.386 |
| Educational Diversity (Simpson) | 0.716 | 0.262 | 0.250 | 1.000 |
| Education Level Diversity (Shannon) | 0.333 | 0.362 | 0.000 | 1.099 |
| Education Level Diversity (Simpson) | 0.770 | 0.247 | 0.333 | 1.000 |

# G: Shannon-Wiener and Simpson Index Values

Table G

*Shannon-Wiener and Simpson index values for diverse strings.*

| | Shannon-Wiener | Simpson |
|---|---|---|
| AA | 0.0000 | 1.0000 |
| AB | 0.6931 | 0.5000 |
| AAA | 0.0000 | 1.0000 |
| ABA | 0.6365 | 0.5556 |
| ABC | 1.0986 | 0.3333 |
| AAAA | 0.0000 | 1.0000 |
| ABAA | 0.5623 | 0.6250 |
| ABCA | 1.0397 | 0.3750 |
| ABCD | 1.3863 | 0.2500 |
| AAAAA | 0.0000 | 1.0000 |
| ABAAA | 0.5004 | 0.6800 |
| ABCAA | 0.9503 | 0.4400 |
| ABCDA | 1.3322 | 0.2800 |
| ABCDE | 1.6094 | 0.2000 |

## H: Covariate Statistics in the Cox Proportional-Hazard Model

Table H

*Direct effects of covariates on new venture failure in the Cox proportional-hazard model.*

| | | | | 95% C.I. for Exp(B) | |
|---|---|---|---|---|---|
| | B | Sig. | Exp(B) | Lower | Upper |
| Level of education diversity | | | | | |
| Model 1 | -0.288 | 0.604 | 0.750 | -1.378 | 0.801 |
| Model 2 | -0.325 | 0.532 | 0.723 | -1.342 | 0.693 |
| Model 3 | -0.322 | 0.534 | 0.724 | -1.339 | 0.694 |
| Model 4 | 0.358 | 0.652 | 1.431 | -1.197 | 1.914 |
| Model 5 | 0.417 | 0.576 | 1.517 | -1.044 | 1.877 |
| Model 6 | 0.414 | 0.578 | 1.513 | -1.046 | 1.874 |
| Number of co-founders | | | | | |
| Model 1 | 0.006 | 0.977 | 1.006 | -0.409 | 0.422 |
| Model 2 | 0.039 | 0.850 | 1.040 | -0.368 | 0.447 |
| Model 3 | 0.040 | 0.847 | 1.041 | -0.368 | 0.448 |
| Model 4 | 0.023 | 0.912 | 1.023 | -0.379 | 0.424 |
| Model 5 | 0.033 | 0.870 | 1.033 | -0.358 | 0.424 |