Start-up Financing: How to Attract the "Right" Investors

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Doctoral Thesis

Submitted to Justus Liebig University Giessen

Department for Technology, Innovation, and Start-up Management

On the 6th of May 2021

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List of Abbreviations

BBSR	Federal Office for Building and Regional Planning
CI	Confidence Interval
Destatis	German Federal Statistical Office
ICO	Initial Coin Offering
IPO	Initial Public Offering
OR	Odds Ratio
R&D	Research and Development
S.E.	Standard Errors
USPTO	United States Patent and Trademark Office
VIF	Variance Inflation Factor
WIPO	World Intellectual Property Organization

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1 General Introduction

1.1 Relevance of the Topic and Research Aim

Scholars and policy makers agree on the importance of start-ups for society because start-ups can create jobs, increase wages, and generate wealth in both stagnant and emerging economies (Audretsch and Moog, 2020; Colombelli, 2016). Despite this acknowledged value of start-ups, we observe a diminishing share of entrepreneurs. In Germany, the proportion of entrepreneurs decreased from 2.76% percent in the year 2002 to 1.17 percent in 2019 (Metzger, 2020), which can result in long-term negative effects for the economy (Alon et al., 2018).

This decline can be due to the potential that entrepreneurs detect entry barriers to founding a start-up, such as fear of failure and fear of debt (Robertson et al., 2003). These fears arise because starting a business comes along with several liabilities, which create situations of high uncertainty (e.g., Baum and Silverman, 2004; Huyghebaert and Van de Gucht, 2007). Typical liabilities that can lead to start-up failure include the liabilities of newness, size, owner centricity, innovativeness, and adolescence (Brettel et al., 2009). Research emphasizes that the liabilities of newness and smallness are especially relevant in this regard because both types of liabilities limit the access of start-ups to external financing (Baum et al., 2000; Davila et al., 2003). Liabilities of newness and smallness refer to the start-ups' lack of resources and unstable relationships (Baum et al., 2000; Hyytinen et al., 2015). In terms of liability of newness, Stinchcombe (1965) argues that new organizations such as start-ups have a higher risk of failure than incumbent organizations. Hence, four reasons are defined to explain the high risk of failure of start-ups (Stinchcombe, 1965). Start-ups have to (1) learn new social roles, (2) establish standard social routines, (3) develop ties with unknown suppliers, and (4) build a corporate identity. Liability of smallness relates to the start-ups' lack of tangible and intangible assets (Freeman et al., 1983; Lefebvre, 2020), which generates disadvantages for attracting financial capital (Aldrich and Auster, 1986).

From the beginning, start-ups have to overcome the scarcity of financial resources to ensure survival. To receive financial resources, start-ups turn to the financial market and compete for debt and equity financing (Carpenter and Petersen, 2002). On the financial market, we observe that investments are mutual decisions that require the approval of both actors (Sørensen, 2007). According to the first side of this matching model, start-ups select investors because different (types of) investors provide different advantages. For example, in addition to financial resources, different types of investors provide diverse value-adding activities (e.g., Dushnitsky and Lenox, 2006; Politis, 2008; Sapienza et al., 1996). Value-adding activities refer to investors' non-financial activities that support the investees, such as providing management skills, coordination, and management control (e.g., Politis, 2008; Sapienza, 1992). According to the second side of the matching model, investors select the most promising start-ups by conducting scouting activities and observing signals from start-ups before the investment transpires (Baum and Silverman, 2004).

This dissertation draws on the logic of start-up financing as a two-sided matching model (Sørensen, 2007). The overarching aim of this dissertation is to shed further light on start-up financing by analyzing both sides of this two-sided matching model. Following this approach is expected to provide clearer guidance for start-ups in terms of which specific types of investors to pursue and the means of attracting them. This knowledge might help start-ups to more likely survive and become more successful in the long term, which is beneficial for the society.

On the financial market, information asymmetries explain why many start-ups encounter limited access to financial resources (Honjo et al., 2014). In particular, debt investors such as banks are often unwilling to take the higher risks associated with start-ups; hence, equity investors have to close the funding gaps of start-ups (Ueda, 2004). For example, Uber obtained about US$1.25 million from 29 business angels in the first two years after Uber's foundation (Crunchbase, 2021). A few years later, when Uber was more established and better known, liabilities diminished and information asymmetries decreased, such that debt investors were also willing to invest billion dollar amounts. In fact, Morgan Stanley, Goldman Sachs, Citigroup, and Barclays PLC co-invested US$1.2 billion in 2016 (Crunchbase, 2021). This example illustrates that equity investors play an important role in enabling the continued existence and growth of start-ups. Even though equity financiers are more willing to close the funding gaps of start-ups (Fraser et al., 2015; Gompers and Lerner, 2001), these investors also have the need of reducing information asymmetries before selecting their investees (Hoenen et al., 2014; Momtaz, 2020a). Therefore, the focus of this dissertation is on equity investments such as business angels, venture capitalists, corporate venture capitalists, and initial coin offerings (ICOs).

The remainder of this chapter provides an overview of the literature in the field of start-up financing with a focus on equity investments. As part of this literature review, I derive three research gaps. To conclude this chapter, I outline the approaches of three studies that aim at closing these research gaps. Finally, I provide a synopsis of the structure of this dissertation.

1.2 Literature Review and Research Gaps

In reference to the two-sided matching model in start-up financing (Sørensen, 2007), previous research can be structured by these two sides. The first side of the matching model refers to the manner by which start-ups should select their investors in terms of the investors' effect on the start-up's development. Here, research often pertains to value-adding activities to explain the investors' impact on start-ups. The second side of the matching model refers to the way that start-ups can attract investors. In this regard, research usually analyzes the effectiveness of signals for fundraising success.

1.2.1 Equity Investors' Impact on the Development of Start-ups

In terms of the first side of the matching model, research analyzing the equity investors' impact on the development of start-ups primarily focuses on venture capitalists (see Table A1). Venture capitalists are professional investment firms that collect money from multiple economic actors and invest this money into a portfolio of start-ups (Bruton et al., 2010).

Sapienza (1992) provides one of the initial insights by showing that the involvement of venture capitalists increases the start-ups' self-perceived performance. Several successive studies confirm venture capitalists' positive impact by examining both subjective and objective performance measures (e.g., Bertoni et al., 2011; Nahata, 2008; Stubner et al., 2007). Some researchers also directly compare venture capital-financed and non-venture capital-financed start-ups. These studies reveal that venture capital-financed start-ups grow faster (Engel and Keilbach, 2007; Kelly and Kim, 2018). These positive effects are often attributed to the most important value-adding activities provided by venture capitalists, such as giving business advice, providing access to their network, and serving on the investees' board (Sapienza et al., 1996). Specifically, the on-site involvement of venture capitalists increases both the start-ups' innovation performance and the probability of a successful exit via an initial public offering (IPO) or an acquisition (Bernstein et al., 2016). Ragozzino and Blevins (2016) confirm venture capitalists' influence on a successful exit; however, they further show that this effect depends on the prominence of venture capitalists, number of involved venture capitalists, duration of the investment, and the amount invested by venture capitalists.

However, other studies do not find such a positive effect but rather reveal insignificant differences between venture capital-financed and non-venture capital-financed start-ups (e.g., Chen, 2009; Jelic et al., 2005). Some studies even demonstrate a negative impact of venture capitalists. In fact, venture capitalists negatively affect the performance of their investees during an IPO (Bruton et al., 2010), but they are unable to compensate for these negative effects later as venture capital-financed firms do not perform better in terms of post-IPO performance (Johnson and Sohl, 2012). Due to these inconclusive results, Rosenbusch et al. (2013) conducted a meta-analysis while widening the research scope to firms of all ages. They reveal a positive effect of venture capitalists on firm performance in general but further explain that this effect depends on the age of the considered firms, that is, the positive impact does not hold for start-ups (Rosenbusch et al., 2013). However, Rosenbusch et al. (2013) acknowledge that their meta-analytical results might be skewed because they could not include studies analyzing closed companies. Hence, survival bias might be a problem. Studies avoiding such a survival bias by examining the likelihood of start-up survival, when venture capitalists are involved, are scarce. However, there are some initial insights. By comparing 565 venture capital-financed and 565 non-venture capital-financed start-ups, Manigart et al. (2002) demonstrate that survival chances are not higher among venture capital-financed start-ups. In this context, start-up age seems to play a role because start-ups that are financed earlier by venture capitalists are more likely to survive (Nanda and Rhodes-Kropf, 2013).

A second research stream concentrates on corporate venture capitalists as another form of equity investments (see Table A2). Corporate venture capitalists are subsidiaries of established firms that invest on behalf of their corporate parents (Chemmanur et al., 2014; Dushnitsky and Lenox, 2006). Thus, established firms indirectly take a minority stake in a start-up that remains independent (Block et al., 2018a). In this research field, Gompers and Lerner (2000b) provide first insights as they underscore that start-ups financed by corporate venture capitalists are at least as successful as start-ups financed by venture capitalists. Similarly, Park and Steensma (2012) reveal that corporate venture capitalists increase the likelihood of the successful exit of their investees. These positive effects can be explained by the value-adding activities of corporate venture capitalists, such as providing complementary assets as well as endorsements and attracting additional financiers (e.g., Dushnitsky and Lenox, 2005, 2006; Ivanov and Xie, 2010; Maula et al., 2009). By contrast, Park and Steensma (2012) indicate that corporate venture capital-financed start-ups have a higher likelihood of failure. Additionally, Chemmanur et al. (2014) demonstrate that start-ups financed by corporate venture capitalists are less profitable than start-ups financed by venture capitalists. In a similar vein, corporate venture capitalists are unable to increase their investees' innovation performance as much as venture capitalists do (Park and Bae, 2018). These inconclusive findings imply that the impact of corporate venture capitalists on their investees depends on the success measure. Huang and Madhavan (2020) confirm this assumption by conducting a meta-analysis on the impact of investments by corporate venture capitalists on different success measures, including technological and financial performance. They show that the impact of corporate venture capitalists indeed varies across these success measures (Huang and Madhavan, 2020).

Going beyond these direct effects, additional studies identify factors that determine the impact of corporate venture capitalists on start-ups. Research finds that a strategic fit between investor and investee influences the effectiveness of corporate venture capitalists. Start-ups are more successful if there is a strategic fit with the corporate venture capitalist (Gompers and Lerner, 2000b; Ivanov and Xie, 2010). In a similar vein, Park and Steensma (2012) suggest that corporate venture capitalists are most beneficial if the start-up needs specialized complementary assets. Another relevant contextual factor is the interplay of different types of investors. In this regard, Kang (2019) delves deeper and examines the interplay of corporate venture capitalists and venture capitalists. The author finds that start-ups financed by such syndicates encounter a lower likelihood of a successful exit when the corporate venture capitalist is more influential than the venture capitalist. In addition, Park and Bae (2018) highlight that the innovation performance of start-ups only increases when corporate venture capitalists invest after an initial investment by venture capitalists (Park and Bae, 2018).

A third, but much smaller, research stream relates to the impact of business angels on their investees (see Table A3). Business angels are private investors who generated their net worth from being successful entrepreneurs or managers (Churchill and Lewis, 1983; Rosenbusch et al., 2013). Research suggests that strategic advice, monitoring, resource acquisition, and mentoring are the primary value-adding activities of business angels (Politis, 2008). However, the impact of these activities on the development of start-ups is rather unresolved. The first insights indicate that start-ups financed by business angels grow faster, are more likely to survive, and exit more successfully (Kerr et al., 2014). However, the issue of whether the impact of business angels or that of venture capitalists is more beneficial lacks consensus in research (e.g., Bruton et al., 2010; Johnson and Sohl, 2012).

Nevertheless, the positive impact of business angels is not generally accepted. For example, Levratto et al. (2018) demonstrate that the impact of business angels on start-up growth depends on the comparison group. They find that business angel-financed start-ups grow faster than a random sample but similar to a nearest neighbor sample. This result implies that business angels merely invest in promising start-ups that become more successful either way. Additionally, Johnson and Sohl (2012) show that start-ups that are financed by business angels do not achieve a more successful IPO. Going one step further, research indicates that the positive impact of business angels depends on contextual factors such as the frequency of communication

(Collewaert and Sapienza, 2016) or syndication in terms of co-investments with venture capitalists (Croce et al., 2018).

Taken together, regarding the first side of the two-sided matching model in start-up financing (Sørensen, 2007), research analyzes the manner by which equity investors affect the development of their investees. Most of these studies focus on venture capitalists and their impact on start-up performance (see Table A1). However, given that research finds inconclusive results (e.g., Bertoni et al., 2011; Chen, 2009) and that survival bias affects the major share of these studies (Manigart et al., 2002; Rosenbusch et al., 2013), additional insights into the effects of venture capitalists are needed. The same case is true for the effects of other types of equity investors; although they are also highly relevant in practice (Kollmann et al., 2020), research has widely neglected them thus far. In fact, the first insights into the effects of corporate venture capitalists and business angels are inconclusive and characterized by survival bias as well (see Table A2 and Table A3). Consequently, I derive the following research gap:

> *Research Gap 1: Prior research lacks insights into the impact of different types of equity investors on the survival chances of start-ups.*

1.2.2 Signaling in Start-up Financing

In terms of the second side of the matching model, the focus of research is on the analysis of the effectiveness of signals in start-up financing. On the one hand, research concentrates on signaling in traditional forms of start-up financing. Traditional forms of start-up financing comprise, for example, investments by venture capitalists and business angels (Block et al., 2018a). On the other hand, research examines signaling in modern forms of start-up financing. This research stream contains new forms of start-up financing, such as crowdfunding and ICOs (Adhami et al., 2018; Block et al., 2018a).

Most studies on signaling in start-up financing evaluate the role of signals in venture capital financing when concentrating on traditional forms of start-up financing. In this context, the focus lies on four types of signals to reduce the perceived liabilities of start-ups, namely intellectual, social, human, and organizational capital (see Table A4).

First, intellectual capital refers to intellectual property rights, including patents and trademarks owned by a start-up, which indicate technological quality (Baum and Silverman, 2004). Research widely acknowledges that there is a positive signaling effect of intellectual capital, both in terms of patents (e.g. Baum and Silverman, 2004; Hsu and Ziedonis, 2013) and trademarks (e.g. Block et al., 2014; Zhou et al., 2016). In terms of patents, research indicates that both the number of patents and ownership of at least one patent increase venture capital investments (Mann and Sager, 2007). In this regard, Zhang et al. (2019) reveal that patents are effective signals from the perspective of venture capitalists when patents convey the quality of technology (i.e., a technological signal) or the quality of protection (i.e., a legal signal). Patents as a signal for business prospects (i.e., a commercial signal) are less relevant (Zhang et al., 2019). However, the signaling effect of intellectual capital lacks consensus in research. Hoenig and Henkel (2015) emphasize that intellectual capital attracts venture capitalists through its property rights function but not its signaling function. Therefore, investors invest in patenting firms because of the patents' productive value as property right; patents as a signal for technological quality are less relevant (Hoenig and Henkel, 2015). In terms of trademarks, research finds that this intellectual property can attract venture capitalists as well (Block et al., 2014). However, the combination of trademarks and patents is an even more effective signal for attracting venture capital investments (Zhou et al., 2016).

Going beyond these direct effects, scholars analyze the relevance of intellectual capital signals by focusing on contextual factors that determine their signaling value. For instance, studies show that the positive effect of patents holds true for both patent applications and patent grants (Lahr and Mina, 2016). However, patent applications have a stronger signaling value than granted patents in attracting venture capital (Haeussler et al., 2014). Moreover, the signaling effect depends on the financing round, as the signaling value diminishes after the first investment round (Hoenen et al., 2014).

Second, studies evaluating the signaling effect of social capital in a venture capital context find mixed results. Social capital refers to relationships with other actors as expressed by, for example, the start-ups' alliances or the founders' personal networks (e.g., Ahlers et al., 2015; Hsu, 2007). Hsu (2007) indicates that social capital raises the valuations of start-ups. However, Baum and Silverman (2004) restrict this effect to downstream alliances (e.g., with marketing firms) and horizontal alliances (e.g., with competitors); meanwhile, upstream alliances (e.g., with universities) are ineffective signals. On the contrary, Hoenig and Henkel (2015) find that upstream alliances have a positive effect, whereas downstream alliances do not.

Third, research examining the signaling effect of human capital also finds mixed results. Human capital refers to an individual's or a team's stock of knowledge and experience indicating capabilities and skills (Ahlers et al., 2015; Gimmon and Levie, 2010). According to Baum and Silverman (2004), start-ups with higher levels of human capital (i.e., whose chief executive officer is more influential and is also active in other start-ups) receive more venture capital funding. However, Baum and Silverman (2004) also find that the prior founding experience of the chief executive officer has no effect on receiving venture capital. By contrast, Hsu (2007) concludes that prior founding experience increases venture capital investments (see also Ko and McKelvie, 2018), whereas education does not (see also Patzelt, 2010). Franke et al. (2008) contradict this finding and underscore that industry and leadership experience as well as the education of the start-up team drive the evaluation of venture capitalists. Hoenig and Henkel (2015) partly confirm this conclusion and argue that the experience of the start-up team attracts venture capital investments. Furthermore, Kirsch et al. (2009) contradict most of the discussed results, as they cannot confirm a positive signaling effect of education, entrepreneurial experience, or business experience on venture capital investments. These inconclusive findings suggest that certain moderators affect the relationship between human capital signals and venture capital investments. Research to date demonstrates, for example, that the funding round (Ko and McKelvie, 2018) and the team size (Patzelt, 2010) determine the effectiveness of human capital signals.

Fourth, research examining the impact of organizational capital on venture capital financing similarly provides mixed results. I refer to organizational capital as factors such as the start-ups' preparedness and the entrepreneurs' personal commitment or passion in their business, which signal a certain degree of seriousness and market readiness. For example, Chen et al. (2009) reveal that preparedness positively influences venture capital financing, whereas entrepreneurial passion does not. However, Kirsch et al. (2009) cannot confirm the importance of preparedness in venture capital financing, as planning documents are ineffective signals.

To conclude, in terms of the second side of the two-sided matching model in start-up financing (Sørensen, 2007), research examines which signals start-ups can send to attract investors. One sub-stream in this field concentrates on traditional forms of financing, such as venture capital (see Table A4). Studies from this sub-stream examine the effectiveness of signals for intellectual (e.g., Lahr and Mina, 2016), social (e.g., Hsu, 2007), human (e.g., Baum and Silverman, 2004), and organizational (e.g., Chen et al., 2009) capital. Among these literature streams, research pays the most attention to the signals of intellectual capital in terms of knowledge. Hence, a vast amount of studies examine the direct effect of knowledge, as indicated by patents, on financing (e.g., Baum and Silverman, 2004; Mann and Sager, 2007). However, Colombo (2021) argues that contextual factors play an essential role for signaling in start-up financing. In this regard, some studies analyze the contextual factors on the start-up level, which affect the signaling effect of patents (e.g., Haeussler et al., 2014; Lahr and Mina, 2016). Nevertheless, concentrating on the start-up level is insufficient because entrepreneurship (Fritsch and Wyrwich, 2014; Konon et al., 2018), knowledge (Asheim and Coenen, 2005; Jaffe et al., 1993), and venture capital investments (Cheng et al., 2019; Lutz et al., 2013) have regional components. Hence, I derive a second RG, which reads as follows:

Research Gap 2: Prior research lacks insights into the issue of if and how a regional component determines the effects of intellectual capital signals in traditional forms of start-up financing.

In terms of the modern forms of start-up financing, one focal point of research is signaling in crowdfunding. Crowdfunding is a form of financing, in which individuals or groups of individuals (e.g., start-ups) acquire financial resources from a large number of mostly private and unprofessional investors, each of whom invests relatively small amounts (Ahlers et al., 2015). In studies from this research stream, knowledge is often transferred from the venture capital context, and similar conceptual frameworks are investigated. Similar to venture capital research, crowdfunding research concentrates on the analysis of the effectiveness of signals in terms of intellectual, social, human, and organizational capital (see Table A5).

First, research finds mixed results regarding the effectiveness of intellectual capital signals. Ahlers et al. (2015) do not find a positive impact of patents on crowdfunding success, whereas Vismara (2018) indicates that patents only attract sophisticated and early investors but not later investors. Second, there are multiple insights regarding the signaling effect of social capital. In fact, Lukkarinen et al. (2016) conclude that crowdfunders attach importance to other signals than traditional equity financiers because they prefer social capital signals over human capital signals. In this regard, studies demonstrate that the founder's personal network (Mollick, 2014) and the project track record (Skirnevskiy et al., 2017) lead to greater crowdfunding success. However, not all the studies support this positive effect of social capital (Ahlers et al., 2015; Barbi and Mattioli, 2019). Third, many studies explore the signals of human capital in crowdfunding and find relatively consistent results. In fact, research reveals that human capital in the form of a larger board and better education across the board results in greater crowdfunding success (Ahlers et al., 2015). Troise et al. (2020) similarly find that a larger team usually achieves greater crowdfunding success (see also Barbi and Mattioli, 2019), which is a particularly effective signal for late investors (Vismara, 2018). Furthermore, research shows that human capital in terms of professional experience (Barbi and Mattioli, 2019), prior crowdfunding success (Courtney et al., 2017), business education (Piva and Rossi-Lamastra, 2018), and entrepreneurial experience (Piva and Rossi-Lamastra, 2018) can help start-ups to become more successful with their crowdfunding campaign. Fourth, research examines the impact of organizational capital on crowdfunding success. In this context, studies find aspects of organizational capital such as use of media (Courtney et al., 2017), extensive campaign descriptions (Bi et al., 2017), frequent updates (Block et al., 2018b), a finished business plan (Troise et al., 2020), and avoidance of spelling errors (Mollick, 2014), as influencing factors of crowdfunding success.

ICOs constitute another recent focal point of research in the field of signaling in modern forms of start-up financing. Similar to crowdfunding, ICOs refer to an open call for funding. Through an ICO, start-ups raise money from a crowd of investors (Fisch, 2019). In exchange for the investment, investors receive digital tokens (Adhami et al., 2018), which are units of value and often sold in the form of cryptocurrencies (Fisch, 2019). These cryptocurrencies refer to a digital medium of exchange drawing on a distributed ledger technology such as blockchain technology (Chen et al., 2021; Domingo et al., 2020). Research on signaling in the ICO context also adapts research on traditional forms of start-up financing. In fact, studies also highlight social and human capital in their analysis of the effectiveness of signals in ICO fundraising.

First, research differentiates between real-life social capital and digital social in the investigation of the signaling effect of social capital. On the one hand, studies regarding real-life social capital examine how the advisory board of a start-up affects ICO fundraising. Research agrees that there is a positive effect of advisors on ICO fundraising success. In fact, research reveals that both the existence of an advisory team (An et al., 2019; Giudici et al., 2020) and the size of the advisory team (Ante et al., 2018; Giudici and Adhami, 2019) positively affect ICO fundraising success. On the other hand, research regarding digital social capital focuses on the use of social media. Some studies indicate that social media usage is beneficial for ICO fundraising success (An et al., 2019; Momtaz, 2020a; Perez et al., 2020). However, Chen (2019) questions these findings as he shows that social media usage is not a driver of ICO fundraising success.

Second, research provides clear results regarding the impact of human capital on ICO fundraising success. Multiple studies agree that team size (An et al., 2019; Ante et al., 2018; Chen, 2019; Giudici et al., 2020; Giudici and Adhami, 2019; Momtaz, 2020b; Roosenboom et al., 2020), the founders' experience (Giudici and Adhami, 2019), the founders' education (An et al., 2019), and the quality of the management team (Momtaz, 2020a) lead to greater fundraising success through an ICO.

Third, research in the ICO context partly adapts knowledge from research on traditional forms of start-up financing by exploring intellectual capital such as patents (Fisch, 2019). However, research on ICOs rather shifts its focus from intellectual capital towards technological capital, which refers to assets in relation to the start-up's key technology as well as innovation-related knowledge (Villasalero, 2014). Fisch (2019) attributes this shift to the highly technological and innovation-driven environment of ICOs. In the ICO context, technological capital contains aspects such as patents, white papers, and the underlying source code. In terms of patents, Fisch (2019) provides the only insights thus far. He argues that patents are not a success driver of ICOs. In terms of white papers, it is unclear if the existence of a white paper increases ICO fundraising success (e.g., Chen, 2019; Giudici and Adhami, 2019) or not (e.g., Adhami et al., 2018; An et al., 2019). Fisch (2019) goes beyond these general insights and demonstrates that a technical white paper helps start-ups to raise more money via an ICO. In terms of the public source code, research is also in disarray. Multiple studies reveal that publishing the source code leads to greater ICO fundraising success (Adhami et al., 2018; Chen, 2019; Giudici and Adhami, 2019; Roosenboom et al., 2020), whereas other studies cannot confirm this positive effect (Fisch, 2019; Giudici et al., 2020). Given these inconclusive findings, research delves deeper and analyzes the quality of the source code. Both Fisch (2019) and Momtaz (2020a) assert that a high-quality source-code increases ICO fundraising success.

To summarize, another sub-stream of research on the second side of the two-sided matching model in start-up financing concentrates on the effectiveness of signals in modern forms of start-up financing, such as ICOs (see Table A6). This research is in its early stages of development, but studies tend to lean towards the direction that established signals from traditional forms of start-up financing, such as social and human capital (e.g., An et al., 2019; Ante et al., 2018), have positive effects on fundraising success. Aside from these established signals, additional studies concentrate on technological capital as a new form of signals, which is relevant because of the technological environment of the modern forms of start-up financing (Fisch, 2019). However, prior research on technological capital provides ambiguous results and lacks comprehensive examinations of multiple signals. Therefore, research has to delve more deeply into technological capital signals, which leads to the third RG:

> *Research Gap 3: Prior research lacks insights into the issue of whether signals for technological capital are drivers of fundraising success in modern forms of start-up financing.*

1.3 Outline of the Dissertation

Overall, the aim of this dissertation is to extend the literature on equity financing by considering both sides of the two-sided matching model (Sørensen, 2007), thus tackling all the research streams and RGs discussed above. After this general introduction, I present the three studies of this dissertation in the next three chapters.

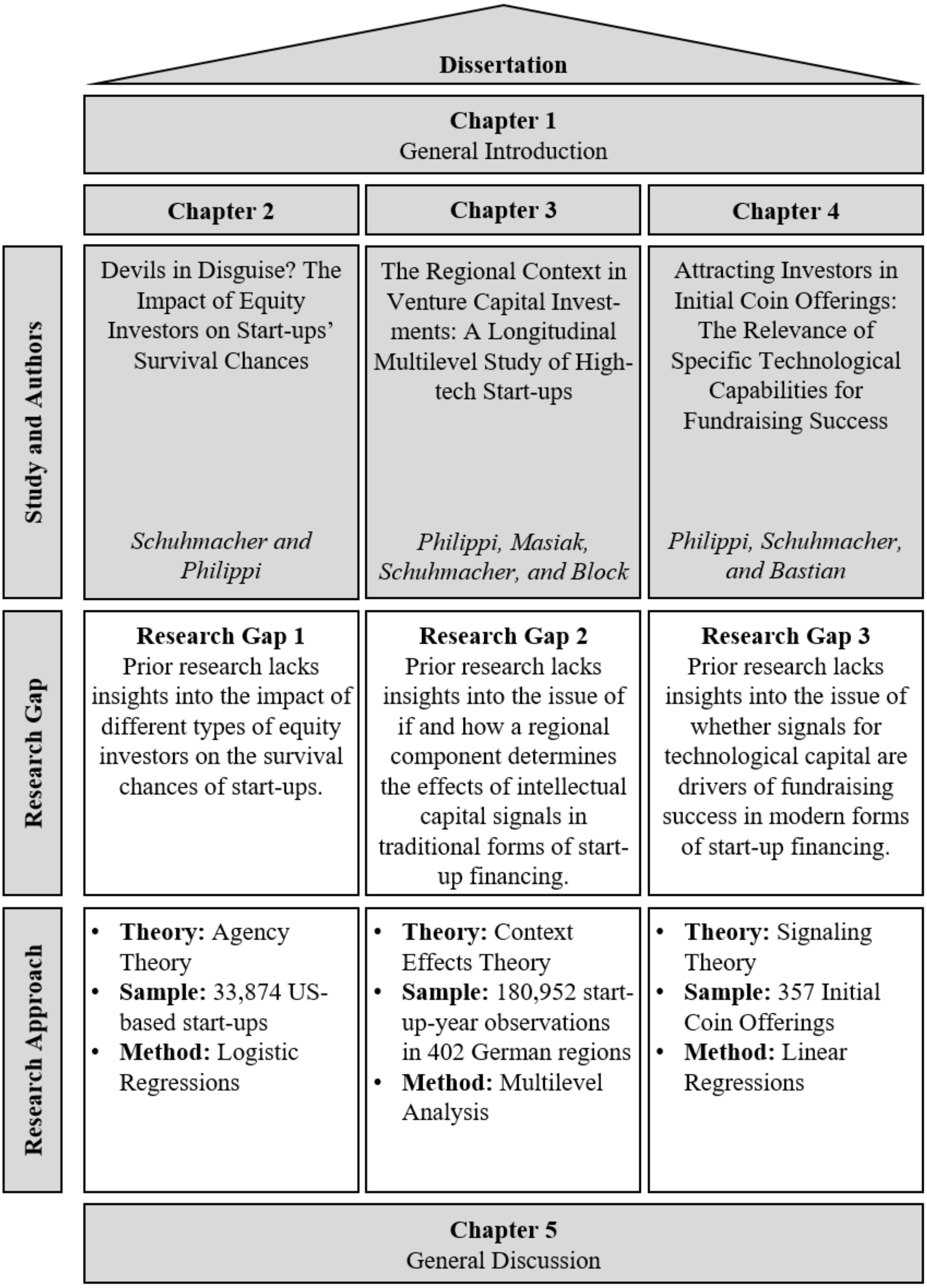
Chapter 2 contains Study 1, which is titled “Devils in Disguise? The Impact of Equity Investors on Start-ups’ Survival Chances.” This study fits into the research stream, which investigates the impact of investors on the development of start-ups, and it is expected to close Research Gap 1 (see Chapter 1.2.1). To tackle the drawbacks of prior research in this area, the specific aim of this study is to clarify the impact of equity investors on start-up survival and the conditions under which equity investors are more or less beneficial for their investees. To achieve that aim, this study draws on agency theory (Jensen and Meckling, 1976). This theory helps to argue that some types of equity investors exhibit congruent goals, whereas others have incongruent goals with their investees (Arthurs and Busenitz, 2003). This goal congruence determines whether equity investors have a positive or a negative effect on start-ups. By examining 33,874 active and closed US-based start-ups via logistic regressions, this study contributes to research by avoiding survival bias and depicting a more realistic picture of the impacts of the different types of equity investors on start-ups.

Chapter 3 includes Study 2, titled “The Regional Context in Venture Capital Investments: A Longitudinal Multilevel Study of High-tech Start-ups.” This study is located in the research field on signaling in start-up financing with a focus on traditional forms of start-up financing. Study 2 is expected to fill Research Gap 2 (see Chapter 1.2.2) by following the specific aim to analyze the interplay of the individual (i.e., start-up) and regional level in venture capital investments. By drawing on context effects theory (Whetten, 2009), the current study argues that the regional knowledge stock and geographical accessibility determine the effectiveness of intellectual capital signals. To test this assumption, this study draws on a sample of 180,952 observations of 46,379 high-tech start-ups located in 402 German regions and conducts a multilevel analysis. In doing so, this study contributes to research by demonstrating whether regional factors can alter the effect of intellectual capital signals, which prior research has neglected thus far.

Chapter 4 comprises Study 3, which is titled “Attracting Investors in Initial Coin Offerings: The Relevance of Specific Technological Capabilities for Fundraising Success.” This study provides new insights into the upcoming research stream on signaling in start-up financing with a focus on the modern forms of start-up financing, and thus tackles Research Gap 3 (see Chapter 1.2.2). The specific aim of this study is to close this research gap by investigating different signal vehicles for technological capabilities and their impact on ICO fundraising success. To do so, this study draws on signaling theory (Spence, 1973) and derives multiple potential signal vehicles that signal technological capital. The effectiveness of these signal vehicles is explored through linear regressions of a sample comprising 357 ICOs. This study contributes to research by providing a more realistic and fine-grained view on the effectiveness of technological capital signals in modern forms of start-up financing.

To conclude, Chapter 5 is a general discussion of the overarching findings and implications of this dissertation. I summarize the structure of this dissertation, including the basic information for each of the three studies, in Figure 1.1.

Figure 1.1: Structure of the Dissertation



2 Devils in Disguise? The Impact of Equity Investors on Start-ups' Survival Chances (Study 1)

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Abstract

Based on agency theory, we argue that goal congruence between start-ups and equity investors is essential for start-ups' survival chances. To test this assumption, we examine a sample of 33,874 US-based active and closed start-ups; this way, we avoid the survival bias that is prevalent in research. Our results suggest that business angels increase their investees' survival chances while venture capitalists and corporate venture capitalists are less beneficial. However, we also reveal that the impacts of all three types of equity investors change along the start-up lifecycle. Additionally, we demonstrate that different combinations of equity investors have varying effects on start-up survival. Thus, we are able to provide guidance for start-ups and equity investors in terms of how to increase the success of equity investments.

Keywords

Start-up survival; Equity financing; Investor syndication; Start-up age; Survival bias

Status

Working Paper

2.1 Introduction

Starting a business not only involves an exciting and auspicious future but also a wide range of risks (Dimov and De Clercq, 2006), which can lead to start-up closure. In fact, less than ten percent of start-ups survive in the long term (Gauthier et al., 2019). Literature discusses several reasons that impede start-ups' survival chances, such as a lack of financial and management resources (e.g., Chatterji et al., 2019; Ruhnka et al., 1992). Start-ups can overcome these lacks by convincing equity investors to invest in their business. On the one hand, equity investors provide financial resources. On the other hand, equity investors bring in management resources by being active investors (Colombo and Grilli, 2010); that is, they help their investees by providing value-adding activities (Politis, 2008).

Value-adding activities refer to equity investors' non-financial activities, such as providing management expertise and access to their network (e.g., Politis, 2008; Sapienza, 1992). Overall, equity investors can help start-ups to overcome lacks of financial resources and management resources, and hence enable increased performance and survival chances of start-ups (Bonini et al., 2019; Colombo and Grilli, 2010). At the same time, however, equity investors' active involvement through value-adding activities involves the danger of conflicts because goals of investors and start-ups can diverge (Brettel et al., 2013). Such conflicts potentially impede start-ups' survival chances. Therefore, although start-ups often desire equity investments, equity investors might be devils in disguise, who are only driven by increasing their own benefits. Thus, the aim of this study is to shed light on the impact of equity investors on start-up survival and the conditions, under which equity investors are more or less beneficial.

In fact, prior research that analyzes the effects of equity investors on a start-up's development (see Table 2.1 for an overview) exhibits two drawbacks. First, the major share of studies inspects the impact of equity investors on start-up performance for active start-ups only (e.g., Bertoni et al., 2011; Stubner et al., 2007). However, concentrating only on active start-ups excludes about 90 percent of start-ups, i.e. closed start-ups (Gauthier et al., 2019). In short, many studies suffer from survival bias (Manigart et al., 2002). Second, equity investment research mainly focuses on venture capitalists (see Table 2.1). Although venture capitalists are among the most prevalent types of equity investors, other equity investors are at least as prevalent (Kollmann et al., 2020). While venture capitalists invested US$ 225 billion in start-ups around the globe in 2019 (KPMG, 2020), corporate venture capitalists invested US$ 57 billion and business angels US$ 50 billion per year in start-ups globally (CBInsights, 2020; Ergocun et al., 2019). Hence, it is not sufficient that research focuses on venture capitalists. Although we observe that some studies examine two equity investors, no study focuses on all three types simultaneously. However, in reality start-ups such as Airbnb often receive investments by multiple types of equity investors (Crunchbase, 2021), which makes this a practically relevant research gap.

Table 2.1: Literature Overview (Study 1)

Source	Closed Firms Considered	Business Angels	Venture Capitalists	Corporate Venture Capitalists	Contextual Factors: Start-up Age	Contextual Factors: Syndi-cation	Dependent Variable
Sapienza (1992)	Not specified	No	**Yes**	No	No	No	• (Non-) Financial performance
Gompers and Lerner (2000a)	Not specified	No	**Yes**	No	No	No	• Valuation
Manigart et al. (2002)	**Yes**	No	**Yes**	No	No	No	• Survival
Jelic et al. (2005)	No	No	**Yes**	No	No	No	• IPO performance
Engel and Keilbach (2007)	Not specified	No	**Yes**	No	No	No	• Growth • Innovation performance
Stubner et al. (2007)	Not specified	No	**Yes**	No	**Yes**	No	• (Non-) Financial performance
Nahata (2008)	Not specified	No	**Yes**	No	No	No	• Exit success
Chen (2009)	No	No	**Yes**	No	No	No	• Financial performance
Bruton et al. (2010)	No	**Yes**	**Yes**	No	No	No	• IPO performance
Bertoni et al. (2011)	**Yes**	No	**Yes**	No	No	No	• Growth
Ivanov and Xie (2010)	Not specified	No	No	**Yes**	No	No	• Valuation
Johnson and Sohl (2012)	Not specified	**Yes**	**Yes**	No	No	No	• IPO performance
Park and Steensma (2012)	**Yes**	No	No	**Yes**	No	No	• Exit success • Bankruptcy
Nanda and Rhodes-Kropf (2013)	**Yes**	No	**Yes**	No	**Yes**	No	• Bankruptcy • IPO performance • Innovation performance
Rosenbusch et al. (2013)	No	No	**Yes**	No	No	No	• Profitability • Growth • Stock market performance
Chemmanur et al. (2014)	No	No	**Yes**	**Yes**	No	No	• Innovation performance
Kerr et al. (2014)	**Yes**	**Yes**	No	No	No	No	• Growth • Survival • Follow-up funding
Bernstein et al. (2016)	Not specified	No	**Yes**	No	No	No	• Innovation performance • Exit success
Collewaert and Sapienza (2016)	No	**Yes**	No	No	No	No	• Innovation performance
Ragozzino and Blevins (2016)	Not specified	No	**Yes**	No	No	No	• Exit success
Croce et al. (2018)	Not specified	**Yes**	**Yes**	No	No	**Yes**	• Follow-up funding • Exit success
Kelly and Kim (2018)	No	No	**Yes**	No	No	No	• Growth
Levratto et al. (2018)	No	**Yes**	No	No	No	No	• Growth
Park and Bae (2018)	Not specified	No	**Yes**	**Yes**	**Yes**	No	• Innovation performance
Bonini et al. (2019)	**Yes**	**Yes**	No	No	No	No	• Performance • Survival
Kang (2019)	Not specified	No	**Yes**	**Yes**	No	**Yes**	• Exit success
Huang and Madhavan (2020)	Not specified	No	No	**Yes**	No	No	• Technological outcomes • Exit success • Financial outcomes
This study	***Yes***	***Yes***	***Yes***	***Yes***	***Yes***	***Yes***	• ***Survival***

Business angels, venture capitalists, and corporate venture capitalists all are active investors with regard to management resources. Nevertheless, these different types of equity investors follow different goals when investing in start-ups. While business angels primarily pursue non-economic goals (Van Osnabrugge, 2000), venture capitalists follow financial goals (Rosenbusch et al., 2013) and corporate venture capitalists emphasize strategic goals (Yang et al., 2014). Some of these goals converge and others diverge with start-ups' goals, which are usually oriented towards the long-term well-being of the business (Churchill and Lewis, 1983). According to agency theory (Jensen and Meckling, 1976), the congruence of goals is essential for the effectiveness of relationships because diverging goals between the principal (i.e. the investor) and the agent (i.e., the start-up), result in ineffective relationships (Arthurs and Busenitz, 2003). In such ineffective relationships, equity investors are unable to provide value-adding activities in an effective manner. Consequently, depending on the equity investors and their major goals, some types of equity investors should be more beneficial for start-ups than other types are. To examine this assumption, we posit the first research question: *To what extent do different types of equity investors affect start-ups' survival chances?*

However, equity investments do not take place in isolation so that contextual factors influence investment success (Rosenbusch et al., 2013). Hence, it is essential to know under which conditions equity investors become more or less beneficial for start-ups. On the one hand, we know that start-ups' goals change along the start-up lifecycle (Churchill and Lewis, 1983). Start-ups rather pursue the goal of stabilizing in early stages, then follow the goal of generating revenues when they grow up, and ultimately seek financial returns further along the lifecycle (Churchill and Lewis, 1983). Due to these changing goals, the extent of agency conflicts with specific types of equity investors should change along the start-up lifecycle. On the other hand, we know that start-ups often receive funding from multiple types of equity investors, i.e. from investor syndicates. In this regard, we follow the term's broad understanding and define investor syndication as the interplay of at least two different types of equity investors who invest in a start-up (Kang, 2019). As different types of equity investors follow different goals, such syndicates bear a risk for multiple goal conflicts, which could impede investment success. Based on these insights, we derive our second research question: *Under which conditions do different types of equity investors affect start-ups' survival chances?*

To answer our research questions, we analyze a sample of 33,874 US-based start-ups, which contains active and closed start-ups. From a practical standpoint, addressing these questions helps us to derive guidance for start-ups and equity investors in terms of how to create successful investment relationships. From a theoretical standpoint, we contribute to research in several ways. First, we are able to overcome drawbacks of prior research to derive meaningful and realistic conclusions regarding the effectiveness of equity investors' involvement for start-up survival. In this regard, this study is the first to focus on active and closed start-ups when analyzing the effects of business angels, venture capitalists, and corporate venture capitalists on start-up survival (see Table 2.1). Thus, we avoid survival bias that affects prior research (Manigart et al., 2002; Rosenbusch et al., 2013). In fact, we demonstrate that existing knowledge needs to be taken with caution because venture capitalists are not as beneficial as often assumed (e.g., Bertoni et al., 2011; Stubner et al., 2007). Second, we test so far uncontested "wisdom" with regard to the impact of different equity investors on start-up survival. Here, we draw on agency theory and develop that goal congruence is essential for the relationships between equity investors and start-ups (Arthurs and Busenitz, 2003; Jensen and Meckling, 1976). In this regard, we extend agency theory by introducing start-up age and syndication as factors that affect goal congruence in investment relationships. Third, existing research is unable to provide clear guidelines when equity investors should invest along the start-up lifecycle. We delve deeper into this topic by showing that start-up age affects the impacts of business angels, venture capitalists, and corporate venture capitalists. Finally, prior research usually concentrates on examining syndication among multiple venture capitalists (e.g., Brander et al., 2002; Dimov and De Clercq, 2006). We, however, consider syndicates of different types of equity investors and demonstrate that the effectiveness of such syndicates depends on the configuration of syndicates.

2.2 Theory and Hypotheses

2.2.1 Agency Theory

Agency theory explains relationships between two parties in a business context. Agency relationships arise when one economic actor, the principal, hires another economic actor, the agent (Jensen and Meckling, 1976). In this context, the principal gives up his decision-making authority so that the agent can perform a task on behalf of the principal (Jensen and Meckling, 1976). However, giving up decision-making authority comes along with asymmetric information to the disadvantage of the principal because the principal cannot fully control the agent's actions (Amit et al., 1990). Since agency theory rests on the assumption that self-interest drives human behavior, there is a risk that the agent performs actions, which may harm the principal (Jensen and Meckling, 1976). These actions arise because principal and agent can pursue differing goals, which results in ineffective relationships between both parties (Arthurs and Busenitz, 2003). By contrast, agency problems do not arise when agent and principal follow congruent goals, resulting in more effective relationships (Arthurs and Busenitz, 2003).

Agency theory helps to explain relationships between start-ups and investors as well. In this context, start-ups function as agents and investors as principals (Kaplan and Strömberg, 2001).

Equity investors are principals in these relationships because they use their money to hire start-ups that should multiply the invested money. Therefore, start-ups have the ability to use the investors' money and may perform activities out of self-interest that can be harmful to investors who aim at protecting the investment (Arthurs and Busenitz, 2003). These agency problems can arise because goals of start-ups and investors differ. In fact, start-ups aim at ensuring the long-term well-being of the company (Churchill and Lewis, 1983) while equity investors' goals tend into different directions. Business angels mainly pursue non-economic goals (Van Osnabrugge, 2000), venture capitalists have financial goals (Rosenbusch et al., 2013), and corporate venture capitalists follow strategic goals for the benefit of their parent company (Yang et al., 2014).

2.2.2 Goals of Start-ups

Overall, start-ups' primary focus is to ensure the long-term well-being of the company (Churchill and Lewis, 1983). However, start-ups' goals typically change while they pass through the different stages of the start-up lifecycle. This lifecycle consists of the following stages: (1) existence, (2) survival, (3) success, (4) take-off, and (5) resource maturity (Churchill and Lewis, 1983). In the first stage, start-ups are very small and try to stabilize their production or offering to gain customer acceptance (Kazanjian, 1988). Start-ups often fail in this stage because they run out of capital; therefore, start-ups primarily aim at staying alive in the first stage (Churchill and Lewis, 1983). In the second stage, start-ups are still small but they start gaining customers (Picken, 2017). Here, start-ups aim at survival but also focus on increasing sales and revenues as many start-ups are unable to develop economic viability and have to close their operations (Churchill and Lewis, 1983). In the third stage, start-ups reach a sufficient size and pursue to scale their business and become profitable (Picken, 2017). Hence, start-ups aim at maintaining the profitable status quo because they can fail if they cannot adapt to environmental changes (Churchill and Lewis, 1983; Kazanjian, 1988). In the fourth stage, start-ups become extensive systems and typically continue to grow (Churchill and Lewis, 1983). In the final stage, start-ups professionalize their business and arrive at a state of maturity (Kazanjian, 1988). These start-ups aim at generating returns on investments and becoming market leaders (Churchill and Lewis, 1983).

2.2.3 Hypotheses Development

By drawing on agency theory (Jensen and Meckling, 1976), we argue that some types of equity investors have congruent goals with start-ups, whereas other types of equity investors have incongruent goals, which should lead to more or less effective investment relationships

(Arthurs and Busenitz, 2003). This variation in the effectiveness of relationships should result in varying effects of investor involvement on start-ups' survival chances. Effective relationships between investors and investees should be beneficial for start-ups because equity investors can conduct their value-adding activities, such as supervising and mentoring (Politis, 2008), more effectively and with higher quality. In turn, we know that high-quality value-adding activities by investors contribute to their investees' survival chances (Pommet, 2017).

Beyond these direct effects, we propose that start-ups' goals change with an increasing age, and thus the effectiveness of relationships with equity investors should change. Furthermore, we argue that the risk of multiple goal conflicts arises when syndicated investments in start-ups take place, which should lead to less effective relationships and impede start-ups' survival chances.

2.2.3.1 The Effect of Equity Investors on Start-up Survival

Business angels are private investors, who generated their net worth from being successful entrepreneurs or managers (Churchill and Lewis, 1983; Rosenbusch et al., 2013). As business angels invest their own money, they are more patient than venture capitalists, who invest money from other investors (Van Osnabrugge, 2000). Even though business angels strive for financial returns to some extent, they primarily follow non-economic goals when investing in start-ups (Van Osnabrugge, 2000). In fact, business angels want to be a part of the entrepreneurial process again and "give something back" to entrepreneurs (Rosenbusch et al., 2013; Van Osnabrugge, 2000).

Business angels aim at developing long-term relationships with their investees (Politis, 2008; Van Osnabrugge, 2000). San José et al. (2005) verify business angels' strong involvement in start-ups by revealing that business angels allocate more than 25 hours per month to each investee. To keep this involvement manageable, business angels usually focus on a limited number of investees (Paul et al., 2007b). As a result, Politis (2008) regards business angels as "co-entrepreneurs" who establish less formal but more empathetic relationships with start-ups than other types of investors (Fairchild, 2011).

While acting as "co-entrepreneurs", business angels follow similar goals as entrepreneurs because business angels and entrepreneurs are often similar in terms of their personality and way of thinking (Politis, 2008). Business angels' activities usually aim at protecting the start-ups' assets and ensuring future survival (Politis, 2008), which are also main goals of start-ups (Churchill and Lewis, 1983). According to agency theory (Jensen and Meckling, 1976), this goal congruence between business angels and start-ups reduces the risk for agency conflicts and improves the effectiveness of their relationships (Arthurs and Busenitz, 2003), resulting in more effective value-adding activities by business angels. To conclude, we argue that business angels and start-ups follow similar goals (Churchill and Lewis, 1983; Politis, 2008). Consequently, we expect that investments by business angels increase start-ups' survival chances because more effective relationships emerge. Thus, we hypothesize:

Hypothesis 1a: Start-ups funded by business angels exhibit a higher probability of survival than start-ups not funded by business angels.

Venture capitalists are professional investment firms who collect money from multiple investors and invest this money in a portfolio of start-ups (Bruton et al., 2010). In other words, venture capitalists do not invest in start-ups as independently as business angels because venture capitalists have to meet their investors' expectations by generating short-term financial returns (Croce et al., 2018; Rosenbusch et al., 2013). Thus, venture capitalists aim for an exit through IPO or acquisition to pay off their investors and redeploy the capital gains to new investments (Bruton et al., 2010). To conclude, generating financial returns is venture capitalists' main goal while non-financial goals do not prevail (Chemmanur et al., 2014; Van Osnabrugge, 2000).

Moreover, venture capitalists' strategy to invest in large portfolios of start-ups can lead to problems in relationships between venture capitalists and start-ups. Because of this portfolio approach, venture capitalists tend to be only interested in the success of the portfolio while the survival of an individual start-up is less important (Manigart et al., 2002). In fact, the major share of venture capitalists' portfolio start-ups fail while the best ten percent of start-ups generate 85 percent of returns (Sahlman, 2010). These statistics imply that venture capitalists rather focus on start-ups in their portfolio that perform as expected (Manigart et al., 2002). Hence, venture capitalists concentrate on adding value to these star performers, who offset the losses generated from investments in failing start-ups (Manigart et al., 2002). Thus, the average start-up from a venture capitalists' portfolio might not experience this positive involvement by venture capitalists.

Taken together, we argue that goals of venture capitalists and start-ups diverge because venture capitalists rather focus on fast financial returns while start-ups aim at a long-term well-being of the business (Churchill and Lewis, 1983; Gorman and Sahlman, 1989). Consequently, relationships between venture capitalists and start-ups, and thus venture capitalists' value-adding activities, become less effective. These ineffective relationships become especially detrimental for portfolio start-ups, which do not belong to the group of star performers. By following financial goals, venture capitalists might try to liquidate these low-performing start-ups, which constitute the majority of most portfolios (Sahlman, 2010). Because of this typical liquidation strategy, we expect that venture capitalists, on average, even reduce start-ups' survival chances. Hence, we hypothesize:

Hypothesis 1b: Start-ups funded by venture capitalists exhibit a lower probability of survival than start-ups not funded by venture capitalists.

Corporate venture capitalists refer to established firms indirectly taking a minority stake in start-ups, who remain independent (Block et al., 2018a). Corporate venture capitalists, like venture capitalists, pursue financial goals (Chemmanur et al., 2014; Park and Steensma, 2012). However, corporate venture capitalists face less pressure to generate short-term results because they are subsidiaries of established firms and invest on behalf of their corporate parents (Chemmanur et al., 2014).

Besides financial goals, strategic goals are usually more important for corporate venture capitalists (Chemmanur et al., 2014). In fact, the main goal of most corporate venture capitalists is to strengthen the corporate parent's competitive advantage and maximize the parent's value (Park and Steensma, 2012). For example, corporate venture capitalists invest in start-ups to get access to new ideas and innovations for the corporate parent (Dushnitsky and Shapira, 2010). Hence, corporate venture capital investments are a means for incumbent firms to learn from start-ups. Corporate venture capitalists are driven by the potential to absorb knowledge from start-ups (Belderbos et al., 2018). In other words, corporate venture capitalists follow a strategic goal to exploit the start-up's knowledge for the corporate parent's benefit (Chemmanur et al., 2014). In fact, we see that corporate parents often have higher patenting rates when they are active as corporate venture capitalist (Dushnitsky and Lenox, 2005) while start-ups cannot draw on the corporate parent's knowledge that much (Di Lorenzo and van de Vrande, 2019). As a result, corporate parents usually benefit more from corporate venture capital investments than the start-ups (Huang and Madhavan, 2020).

To conclude, we argue that goals of start-ups and corporate venture capitalists diverge. Start-ups might expect to receive value-adding activities from corporate venture capitalists. These activities should improve the long-term well-being of start-ups, which is one of their majors goals (Churchill and Lewis, 1983). Contrary to that, corporate venture capitalists mainly aim at absorbing and exploiting knowledge from their investees (Chemmanur et al., 2014; Dushnitsky and Lenox, 2005). In many cases, corporate venture capitalists even invest in start-ups with the goal to imitate or acquire the start-up (Drover et al., 2017b). Thus, we expect that corporate venture capitalists are not only unable to increase their investees' survival chances but have a negative impact on survival chances of the average start-up. Accordingly, we hypothesize:

Hypothesis 1c: Start-ups funded by corporate venture capitalists exhibit a lower probability of survival than start-ups not funded by corporate venture capitalists.

2.2.3.2 The Moderating Effect of Start-up Age

Although start-ups primarily aim at the long-term well-being of the business along the whole start-up lifecycle, their goals change over time (Churchill and Lewis, 1983). Start-ups primarily aim at surviving and stabilizing in the early stages while they rather aim at growing and generating returns in the later stages (Churchill and Lewis, 1983). Therefore, goal congruence between equity investors and start-ups can change over time as well.

First, we expect that the positive impact of business angels on start-up survival decreases with increasing start-up age because goals between business angels and start-ups become incongruent while start-ups grow up. Business angels primarily follow non-economic goals when investing in start-ups and they want to be part of the entrepreneurial process to relive the entrepreneurial spirit, which they know from their own time as entrepreneurs (Rosenbusch et al., 2013; Van Osnabrugge, 2000). However, start-ups usually loose this entrepreneurial spirit over time because they become more complex organizations and established market actors, who aim at growing and generating returns (Churchill and Lewis, 1983). Although business angels follow these goals to some extent, the overall degree of goal congruence should decrease over time so that the effectiveness of relationships between business angels and investors decreases (Arthurs and Busenitz, 2003). Relationships might become especially ineffective because founders often disengage from the start-up (Churchill and Lewis, 1983). In such situations, business angels cannot maintain their long-term relationships, which they usually aim for (Politis, 2008; Van Osnabrugge, 2000).

Second, we argue that goal congruence between venture capitalists and start-ups increases when start-ups grow up so that the negative impact of venture capitalists on start-up survival should become weaker. We know that venture capitalists mainly follow financial goals (Rosenbusch et al., 2013). At the same time, start-ups shift their focus towards aiming at growing and generating returns in the later stages (Churchill and Lewis, 1983). Therefore, start-ups' goals become more financially driven over time, which is in line with venture capitalists' goals (Rosenbusch et al., 2013). Often founders might even pursue an exit in the later stages to reap the rewards of their work (Picken, 2017), which is also the ultimate goal of venture capitalists (Bruton et al., 2010).

Third, we assume that goals of corporate venture capitalists and start-ups become more congruent when start-ups become older so that the negative impact of corporate venture capitalists on start-up survival becomes weaker. Corporate venture capitalists follow financial goals but also emphasize strategic goals (Yang et al., 2014). Start-ups' shift towards financial goals in the later stages (Churchill and Lewis, 1983) should result in greater goal congruence between corporate venture capitalists and grown-up start-ups. In fact, corporate venture capitalists' strategic goals might be less deterrent for their investees in many cases.

Following the arguments of agency theory (Arthurs and Busenitz, 2003; Jensen and Meckling, 1976), these changes over time should result in decreasing goal congruence between business angels and start-ups while goal congruence between start-ups and (corporate) venture capitalists should increase. Hence, we hypothesize:

> *Hypothesis 2: Start-up age moderates the effect of equity investors on the probability of start-up survival, such that the growing up of a start-up weakens the (a) positive impact of business angels, (b) the negative impact of venture capitalist, and (c) the negative impact of corporate venture capitalist on the probability of start-up survival.*

2.2.3.3 The Moderating Effect of Investor Syndication

Start-ups often receive investments from different types of equity investors (Kollmann et al., 2020). For example, Airbnb acquired resources from venture capitalists, corporate venture capitalists, and business angels in the early years of existence (Crunchbase, 2021). However, based on agency theory we propose that syndicated investments can be problematic for start-ups.

When syndicated investments take place, different types of equity investors have to cooperate while pursuing their own goals. Here, goals of different types of equity investors also diverge in terms of non-economic, financial, and strategic goals (Chemmanur et al., 2014; Rosenbusch et al., 2013; Van Osnabrugge, 2000). These diverging goals can evoke conflicts of interest, which go beyond conflicts between start-ups and a single type of equity investor. In other words, additional conflicts of interests may occur within syndicates composed of different types of equity investors (e.g., Chahine et al., 2012). These conflicts within syndicates may increase agency conflicts because start-ups have to balance out their own goals with multiple, possibly opposing, goals by equity investors.

Following the logic of agency theory (Jensen and Meckling, 1976), these diverging goals between start-ups and investors reduce the effectiveness of investment relationships (Arthurs and Busenitz, 2003), and thus equity investors' value-adding activities. Syndicates might even fuel the risk of startup failure because the different types of equity investors are busy to enforce their own goals over other equity investors' goals while not minding the start-up's well-being. Therefore, we expect that the impact of equity investors becomes (more) detrimental for start-ups survival chances when investments are syndicated. Hence, we hypothesize:

Hypothesis 3: Investor syndication moderates the effect of equity investors on the probability of start-up survival, such that syndication weakens the positive impact of (a) business angels, and strengthens the negative impact of (b) venture capitalist as well as (c) corporate venture capitalist on the probability of start-up survival.

2.3 Methodology

2.3.1 Sample and Data Sources

To test our hypotheses, we use data from Crunchbase, which is an American data aggregator. Crunchbase contains data on companies from around the world, including company characteristics (e.g., status), funding rounds (e.g., type of financing round), and investors (e.g., type of investor). Academia conceives Crunchbase as a precise and reliable source of data leading to a vast amount of studies drawing on this database (e.g., Chatterji et al., 2019; Marx and Fuegi, 2020).

We use the database as of August 2017, which contains information on 153,311 companies of every age. To fit the needs of our research model, we conducted several steps of data adjustment. First, we eliminated all firms located outside of the US, resulting in a preliminary sample of 82,150 US-based companies. Besides their outstanding status within the Western start-up ecosystem, the US were chosen in accordance with relevant studies in the research field of entrepreneurial finance (e.g., Alvarez-Garrido and Dushnitsky, 2016; Park and Steensma, 2012). Then, we excluded all companies that were older than 10 years because our study concentrates on start-ups (e.g., Forbes, 2005). This step lead to a preliminary sample of 43,647 US-based start-ups. Finally, we excluded all cases with missing values, resulting in a final sample of 33,874 US-based start-ups.

2.3.2 Variables

2.3.2.1 Dependent Variable

As dependent variable, we operationalize *start-up survival* as a dichotomous variable. This variable differentiates if the respective start-up did not fail (i.e., is still running) or failed (i.e., stopped running during the first 10 years of existence). This way, we account for failed start-ups and overcome survival bias (for a similar measurement, see Cooper et al., 1994). Crunchbase categorizes firms as “closed”, “operating”, “acquired”, or “IPO”. Because we define start-up survival as start-ups that did not fail, the variable *start-up survival* takes the value one for “operating” and successfully exited start-ups, that is, “acquired” start-ups as well as start-ups that underwent an “IPO”. Consequently, the variable takes the value zero if Crunchbase categorizes a start-up’s status as “closed”.

2.3.2.2 Independent Variables

For the main effects of different types of equity investors, we utilize three dummy variables. The variable *business angel* takes the value one if at least one business angel funded the respective start-up. We calculate the dummy variables *venture capitalist* and *corporate venture capitalist* likewise. Thus, we adopt the approach by several studies analyzing dummy variables to capture if a specific type of investor invests in a start-up (e.g., Vanacker et al., 2013).

As our proposed moderator, we consider the variable *start-up age* that reflects a start-ups’ maturity. To operationalize this variable, we observe the number of years a start-up has been operating since its foundation (e.g., Hsu and Ziedonis, 2013). Finally, for *syndication*, we create another dummy variable, which takes the value one if a syndicate composed of at least two different types of equity investors invested in the start-up during the period of the first 10 years after the start-up’s foundation.

2.3.2.3 Control Variables

Further, we include multiple control variables in our analyses. First, we consider the variable *number of rounds*, which refers to the number of financing rounds the respective start-up has passed through (e.g., Gimmon and Levie, 2010). This variable reflects the development of a start-up and its advancement through the funding lifecycle. Due to increased financial resources through multiple financing rounds, start-up survival should become more likely. Second, we consider the *number of investors*, which contains the overall number of investors involved in the start-up. This allows us to control for the size of investor syndicates, which is shown to affect firm performance (Falconieri et al., 2019). Third, we include *start-up size* as control variable, which is, due to the Crunchbase database, a categorical variable consisting of nine groups, depending on the start-up's number of employees. We control for this effect because scholars have revealed that small firms are more likely to fail (e.g., Kalleberg and Leicht, 1991). Finally, based on the classifications by Crunchbase, we assign all start-ups to at least one of 36 *industry dummies* to control for industry effects. Start-ups' approaches, should be roughly alike within an industry, which may explain why survival rates vary across industries (Audretsch, 1991). Hence, we follow existing studies on start-up survival and performance by controlling for the industry (e.g., Dimov and De Clercq, 2006).

2.4 Results

2.4.1 Descriptive Statistics

Table 2.2 reveals descriptive statistics and bivariate correlations. Overall, there are no problematic correlations among our variables. The highest correlation can be found between the variables syndication and business angel (r = .683). To check for multicollinearity, we also examine the variance inflation factors (VIFs). We find that all variables score VIFs below a value of five, which is a typical threshold to assess multicollinearity problems. Overall, the average VIF amounts to 1.830 for the full model including industry dummies. These findings indicate that there are no problems of (multi)collinearity, which bias our results.

Table 2.2: Descriptive Statistics and Correlations (Study 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	VIF	Mean	S.D.	Min	Max
Dependent Variable														
(1) *Start-up Survival*	1.000									-	.923	.264	0	1
Control Variables														
(2) *Number of Funding Rounds*	.062	1.000								4.87	2.061	1.591	1	22
(3) *Number of Investors*	.042	.588	1.000							3.24	3.669	6.045	0	95
(4) *Start-up Size*	.084	.231	.255	1.000						3.39	1.934	1.324	1	9
Independent Variables														
(5) *Business Angel*	.045	.252	.473	.020	1.000					3.02	.238	.426	0	1
(6) *Venture Capitalist*	.019	.394	.536	.230	.267	1.000				3.09	.441	.496	0	1
(7) *Corporate Venture Capitalist*	.020	.258	.396	.162	.110	.245	1.000			1.72	.070	.255	0	1
(8) *Start-up Age*	.095	.448	.241	.326	.011	.225	.156	1.000		4.32	3.755	2.535	1	10
(9) *Syndication*	.044	.375	.627	.127	.683	.552	.487	.124	1.000	4.63	.197	.398	0	1

2.4.2 Main Analyses

We run multiple moderated regressions to test our hypotheses. In fact, we conduct binary logistic regressions because of the binary nature of the dependent variable. Model 1 (see Table 2.3) contains the control variables including industry dummies, whose individual effects are not displayed for reasons of simplicity. The results reveal that the number of funding rounds (B = .114, S.E. = .023, p = .000) and start-up size (B = .346, S.E. = .035, p = .000) increase the probability of start-up survival, whereas the number of investors does not have a material effect on start-up survival (B = –.005, S.E. = .005, p = .269). When we calculate the corresponding odds ratio (OR) by exponentiation of these coefficients, we are able to interpret the economic magnitude of these effects. In fact, an additional financing round results in a 12.1 percent increase of survival chances (OR = 1.121). Similarly, when start-up size increases by one unit, survival chances of a start-up increases by 41.3 percent (OR = 1.413).

In Model 2 (see Table 2.3), we add the three types of equity investors as well as the direct effects of our hypothesized moderators to the regression. First, the results reveal that business angels positively contribute to the probability of start-up survival (B = .351, S.E. = .084, p = .000). The OR shows that start-ups that are financed by business angels are 42 percent (OR = 1.420) more likely to survive than start-ups that are not financed by business angels. Thus, we find support for Hypothesis 1a. Second, venture capitalists decrease the probability of start-up survival (B = –.288, S.E. = .053, p = .000), i.e. the probability of survival is 25 percent lower for venture capital-financed start-ups than for start-ups that are not financed by venture capitalists (OR = .750). Therefore, the results are in line with our predictions so that we find support for Hypothesis 1b. Third, we find a negative effect of corporate venture capitalists on start-up survival (B = –.197, S.E. = .114, p = .085). Specifically, start-ups financed by corporate venture capitalists are 17.9 percent less likely to survive than start-ups that are not financed by corporate venture capitalists (OR = .821). Although this effect is the smallest among all equity investor effects, we still find support for Hypothesis 1c. Additionally, Model 2 shows that a higher start-up age results in higher chances of start-up survival (B = .118, S.E. = .012, p = .000). Specifically, an increase of start-up age by one year, leads to an increase of start-up survival chances by 12.5 percent (OR = 1.125). Similarly, we observe that start-ups survive more likely when they receive financial resources via syndicated investments (B = .294, S.E. = .112, p = .009). In fact, start-ups that receive syndicated investments are 34.2 percent more likely to survive than start-ups that do not receive syndicated investments (OR = 1.342).

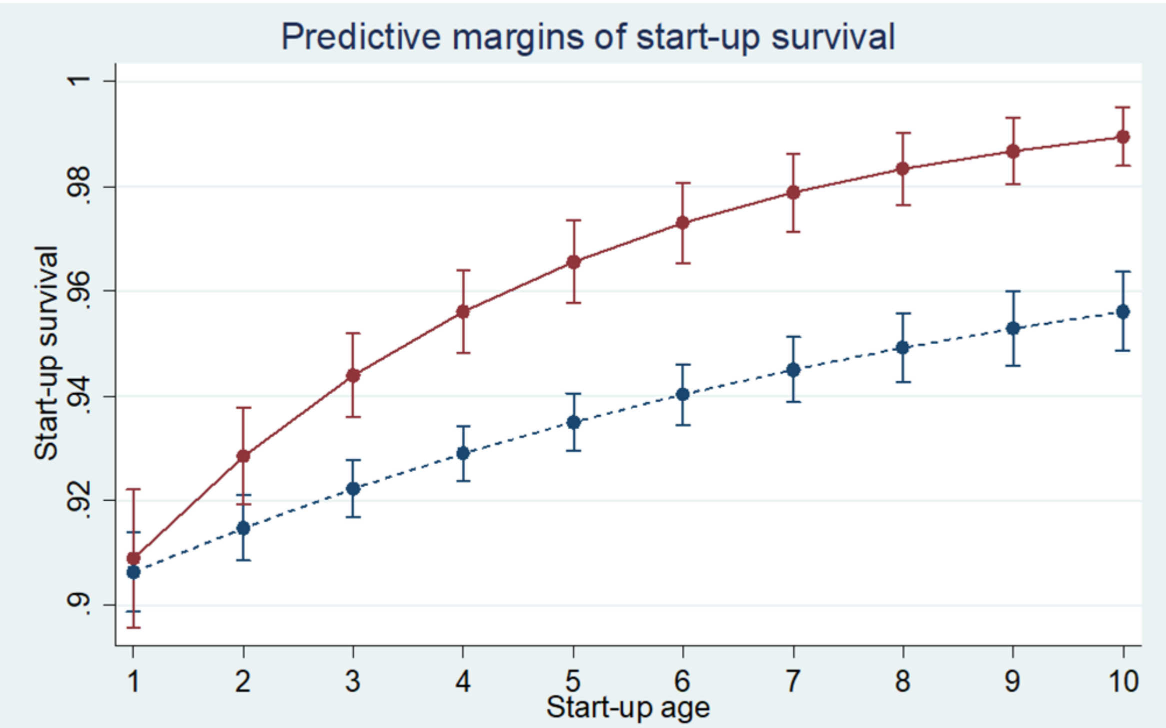
Table 2.3: Logistic Regression Results (Study 1)

	Model 1				Model 2				Model 3			
	B	**(S.E.)**	**p**	**[95% CI]**	**B**	**(S.E.)**	**p**	**[95% CI]**	**B**	**(S.E.)**	**p**	**[95% CI]**
Constant	1.368	(.073)	.000	[1.225; 1.511]	1.221	(.072)	.000	[1.080; 1.361]	1.119	(.079)	.000	[.964; 1.274]
Control Variables												
Number of Funding Rounds	.114	(.023)	.000	[.068; .159]	.046	(.024)	.054	[–.001; .093]	.055	(.024)	.022	[.008; .103]
Number of Investors	–.005	(.005)	.269	[–.015; .004]	–.015	(.006)	.013	[–.027; –.003]	–.013	(.007)	.045	[–.026; –.000]
Start-up Size	.346	(.035)	.000	[.278; .414]	.305	(.035)	.000	[.236; .374]	.311	(.036)	.000	[.241; .381]
Independent Variables												
Business Angel					.351	(.084)	.000	[.185; .516]	–.109	(.113)	.335	[–.330; .113]
Venture Capitalist					–.288	(.053)	.000	[–.392; –.185]	.020	(.088)	.818	[–.152; .193]
Corporate Venture Capitalist					–.197	(.114)	.085	[–.421; .027]	.839	(.364)	.021	[.126; 1.552]
Start-up Age					.118	(.012)	.000	[.094; .142]	.151	(.017)	.000	[.119; .184]
Syndication					.294	(.112)	.009	[.075; .514]	–.231	(.711)	.745	[–1.626; 1.163]
Interactions												
Business Angel X Start-up Age									.164	(.037)	.000	[.091; .237]
Venture Capitalist X Start-up Age									–.101	(.023)	.000	[–.145; –.057]
Corporate Venture Capitalist X Start-up Age									–.120	(.044)	.006	[–.206; –.034]
Business Angel X Syndication									–.152	(.252)	.547	[–.646; .342]
Venture Capitalist X Syndication									.609	(.634)	.337	[–.633; 1.850]
Corporate Venture Capitalist X Syndication									–.580	(.392)	.139	[–1.349; .189]
Industry Dummies	Yes				Yes				Yes			
Chi ²	590.96 (p = .000)				795.76 (p = .000)				778.90 (p = .000)			
Pseudo R²	.047				.570				.606			
Log Pseudolikelihood	–8,616.234				–8,521.944				–8,489.577			
No. of Observations	33,874				33,874				33,874			

Notes: We calculated robust standard errors (S.E.); dependent variable: start-up survival (dummy); CI = Confidence Interval.

Model 3 (see Table 2.3) adds the interaction terms to the regression. Regarding the moderating effect of start-up age, we find mixed results. First, we see that start-up age enhances the survival-increasing impact of business angels (B = .164, S.E. = .037, p = .000). Figure 2.1 illustrates this effect and reveals that survival chances of start-ups that receive funding from business angels increases with start-up age. Based on conditional marginal effects (see Figure 2.1), we are able to derive more detailed conclusions. Differences in survival chances of business angel-financed start-ups and non-business angel-financed start-ups are negligible in the first year of existence (dy/dx = .002, S.E. = .008, p = .801). From the second year on (dy/dx = .013, S.E. = .006, p = .036), this difference becomes material as business angel-financed start-ups survive more likely than non-business angel-financed start-ups. Thus, we find no support for Hypothesis 2a.

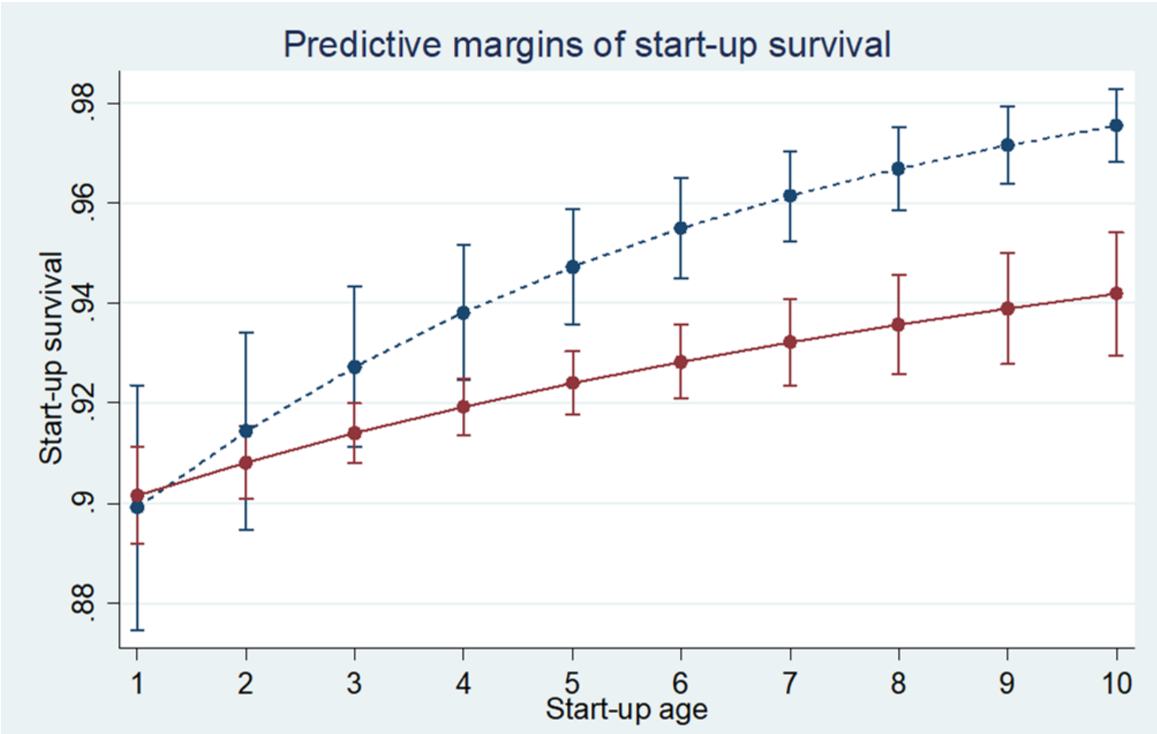
Figure 2.1: Interaction Plot: Business Angel and Start-up Age (Study 1)



dy/dx	.002	.013	.021	.028	.032	.035	.037	.038	.038	.038
S.E.	.008	.006	.006	.006	.006	.007	.007	.007	.007	.007
p	.801	.036	.000	.000	.000	.000	.000	.000	.000	.000

Second, the survival-decreasing effect of venture capitalists increases when start-ups grow up (B = –.101, S.E. = .023, p = .000). Figure 2.2 reveals that survival chances of venture capital-financed start-ups compared to start-ups with no venture capitalist investment do not differ for young start-ups, i.e. in the first three years of existence (first year: dy/dx = .003, S.E. = .011, p = .785; second year: dy/dx = –.004, S.E. = .009, p = .643; third year: dy/dx = –.010, S.E. = .008, p = .192). However, the effect of venture capitalists becomes detrimental with an increasing start-up age. From the fourth year on (fourth year: dy/dx = –.014, S.E. = .006, p = .028), survival chances for non-venture capital-financed start-ups become substantially higher than for venture capital-financed start-ups (see Figure 2.2). Thus, we find no support for Hypothesis 2b.

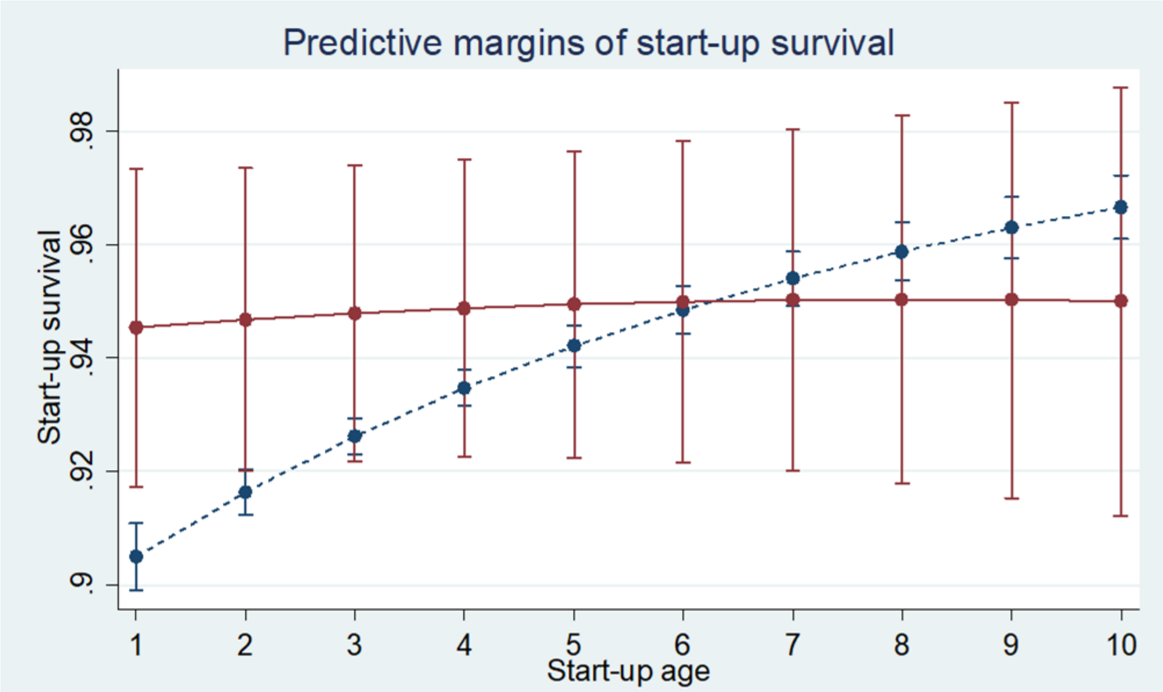
Figure 2.2: Interaction Plot: Venture Capitalist and Start-up Age (Study 1)



dy/dx	.003	-.004	-.010	-.014	-.017	-.019	-.021	-.022	-.022	-.022
S.E.	.011	.009	.008	.006	.006	.005	.005	.005	.005	.005
p	.785	.643	.192	.028	.002	.000	.000	.000	.000	.000

Third, we discover a negative interaction term for corporate venture capitalist and start-up age (B = –.120, S.E. = .044, p = .006). Figure 2.3 shows that investments by corporate venture capitalists are beneficial for start-ups' survival chances in the first two years of existence (first year: dy/dx = .046, S.E. = .022, p = .035; second year: dy/dx = .033, S.E. = .019, p = .082). When start-ups grow up, this effect turns around as start-ups survive less likely when corporate venture capitalists invest (third year: dy/dx = .022, S.E. = .017, p = .188). Though, these differences in the later years turn out to be not significant. Thus, we find no support for Hypothesis 2c.

Figure 2.3: Interaction Plot: Corporate Venture Capitalist and Start-up Age (Study 1)



dy/dx	.046	.033	.022	.013	.006	.000	-.004	-.008	-.010	-.012
S.E.	.022	.019	.017	.015	.014	.013	.012	.012	.011	.011
p	.035	.082	.188	.387	.672	.987	.732	.516	.365	.264

Regarding the moderating effect of syndication, we observe that syndication does not affect the impact of the three types of equity investors on start-up survival. In fact, the interaction terms of syndication with business angels (B = –.152, S.E. = .252, p = .547), venture capitalists (B = .609, S.E. = .634, p = .337), and corporate venture capitalists (B = –.580, S.E. = .392, p = .139) do not affect start-up survival. Hence, we find no support for Hypothesis 3.

2.4.3 Additional Analyses

We were fairly surprised by the finding that syndicated investments do not influence the impact of equity investors on start-up survival. Therefore, we conducted an additional analysis, which delves deeper into syndicated investments. Specifically, we re-run our moderated regression but included all possible combinations of different types of equity investors, which allows us to derive more fine-grained conclusions about the effectiveness of syndicates. Table 2.4 displays the results of this additional analysis.

Table 2.4: Logistic Regression Results for all Types of Syndicates (Study 1)

	Model 1				Model 2			
	B	**(S.E.)**	**p**	**[95% CI]**	**B**	**(S.E.)**	**p**	**[95% CI]**
Constant	1.242	(.071)	.000	[1.104; 1.381]	1.219	(.072)	.000	[1.078; 1.360]
Control Variables								
Number of Funding Rounds	.040	(.024)	.090	[–1.006; 1.086]	.048	(.024)	.043	[.002; .095]
Number of Investors	–.004	(.005)	.466	[–1.013; 1.006]	–.017	(.006)	.007	[–.029; –.005]
Start-up Size	.280	(.034)	.000	[1.213; 1.348]	.306	(.035)	.000	[.237; .376]
Start-up Age	.109	(.012)	.000	[1.085; 1.133]	.118	(.012)	.000	[.094; .142]
Independent Variables								
Business Angel					.274	(.087)	.002	[.104; .444]
Venture Capitalist					–.292	(.053)	.000	[–.396; –.188]
Corporate Venture Capitalist					.443	(.354)	.211	[–.251; 1.137]
Business Angel & Venture Capitalist					.400	(.096)	.000	[.211; .589]
Business Angel & Corporate Venture Capitalist					–.031	(.603)	.958	[–1.213; 1.150]
Venture Capitalist & Corporate Venture Capitalist					–.361	(.133)	.007	[–.622; –.100]
Business Angel & Venture Capitalist & Corporate Venture Capitalist					.302	(.197)	.124	[–.083; .688]
Industry dummies	Yes				Yes			
Chi ²	697.79 (p = .000)				795.42 (p = .000)			
Pseudo R²	.052				.058			
Log pseudolikelihood	– 8,567.736				– 8,517.615			
No. of observations	33,874				33,874			

Notes: We calculated robust S.E.; dependent variable: start-up survival (dummy).

Regarding the different types of syndicates, we find mixed results. In fact, syndicates of business angel and venture capitalist increase start-ups' survival chances (B = .400, S.E. = .096, p = .000). Such syndicates are able to increase start-up's survival chances by 49.2 percent (OR = 1.492), which is the largest positive effect of all equity investors and syndicates. Contrary to that, syndicates of venture capitalist and corporate venture capitalist decrease start-ups' survival chances (B = –.361, S.E. = .133, p = .007). Such syndicates decrease start-ups' survival chances by 30.3 percent (OR = .697), which is the largest negative effect of all equity investors and syndicates (see Table 2.4). All other syndicates do not have an impact on start-up survival.

2.5 Discussion

2.5.1 Key Findings

The aim of this study was to shed light on how equity investors affect start-up survival and conditions, under which equity investors are more or less beneficial for start-ups. In fact, we find that equity investors have varying effects on their investees' survival chances. In other words, some equity investors are angels while others turn out as devils in disguise that are harmful to start-ups.

First, our results demonstrate that business angels increase start-ups' survival chances. Since business angels act as "co-entrepreneurs", they primarily want to protect their investees' assets and ensure future survival (Politis, 2008). These goals are widely congruent with start-ups' goals (Churchill and Lewis, 1983), which leads to effective investment relationships between business angels and start-ups. However, we do not find that business angel-financed start-ups survive more likely along the whole start-up lifecycle. Differently than often argued (Politis, 2008), business angels cannot increase their investees' survival chances in the first year of existence. This negligible difference in the first year might arise because start-ups require knowledge to stabilize their production or offering in this early phase (Kazanjian, 1988). However, business angels rather provide general business expertise than offering-related expertise (Macht and Robinson, 2009), so that business angels' influence pays off in subsequent years. Starting with the second year, start-ups benefit from business angel investments. This finding implies that goal congruence between business angels and start-ups does not decrease with increasing start-up age. Similarly to start-ups, business angels might become more driven by financial goals over time (Churchill and Lewis, 1983) Overall, our results suggest that business angels are indeed angels and no devils in disguise.

Second, we find that venture capitalists decrease their investees' survival chances. Venture capitalists' emphasize financial goals, which is widely incongruent with start-ups' goals (Churchill and Lewis, 1983). Hence, investment relationships between venture capitalists and start-ups cannot become effective. By enforcing their own goals, venture capitalists might impose ill-advised policies, such as replacing team members (Hellmann and Puri, 2002) or providing wrong strategic inputs that hinder the start-up's long-term development (Steier and Greenwood, 1995). Beyond this general negative effect of venture capitalists, this study reveals that the effect does not prevail across the whole start-up lifecycle. Although venture capitalists shifted their focus from early- towards later-stage investments when the venture capital industry matured (Gompers, 1995; Hellmann and Thiele, 2015), we show that venture capitalists are less destructive for start-ups when they invest in the early years (see also Nanda and Rhodes-Kropf, 2013). In the first years of a start-up's life, venture capitalists observe whether the start-up is able to become a star-performer among their portfolio start-ups or a liquidation candidate, which usually represent the major share of venture capitalists' portfolios (Sahlman, 2010). For these liquidation candidates, goal congruence between start-ups and venture capitalists decreases over time because venture capitalists increasingly aim to enforce their financial goals by liquidating them. Contrary to that, start-ups aim to save their business before caring about financial returns for their investors. As a result, incongruent goals characterize relationships between venture capitalists and the majority of portfolio start-ups more when start-ups grow up. Thus, we demonstrate that venture capitalists are usually devils in disguise who reduce start-ups' survival chances especially in the later stages.

Third, our results suggest that corporate venture capitalists have a negative impact on start-up survival. Corporate venture capitalists are driven by the potential to absorb knowledge from start-ups (Belderbos et al., 2018). These strategic goals are incongruent with start-ups' goals of long-term well-being of the business (Churchill and Lewis, 1983) so that investment relationships between corporate venture capitalists and start-ups turn out ineffective (Arthurs and Busenitz, 2003). However, this negative impact is not constant over time as we show that corporate venture capital-financed start-ups survive more likely in the early-stage but this difference diminishes in the later-stage. These insights imply that the relationship between corporate venture capitalists and start-ups becomes less beneficial along the start-up lifecycle. Corporate venture capitalists might focus on providing value-adding activities to young start-ups when their business ideas' potential is uncertain (cf. Huang and Pearce, 2015) and their technology needs to be developed further to benefit the corporate venture capitalist. This way, start-ups are able to advance their business idea and tap into its full potential. In later stages, the potential of start-ups' business ideas for corporate venture capitalists is directly useable. Thus, if corporate venture capitalists evaluate the business idea as promising, they most likely invest because they want to extract knowledge from the start-up to use it for their own benefit instead of spurring the start-up's development. Overall, our results imply that corporate venture capitalists are no devils in disguise because they provide benefits to their investees in the early years and do not decrease start-ups' survival chances in the later years.

Fourth, our findings demonstrate that syndicated investments are a double-edge sword for start-ups because syndicates can have a positive but also a negative effect on start-up survival. In general, we find that syndication positively affects start-ups' survival chances but the effectiveness of such investments depends on the configuration of syndicates. On the one hand, we show that the combination of business angels and venture capitalists is beneficial for start-ups. In such syndicates, venture capitalists likely provide financial resources but are less involved than business angels. Business angels can make use of the money from venture capitalists because venture capitalists usually invest more money than business angels (Statista, 2020, 2021). In other words, venture capitalists and business angels rely on each other (see also Hellmann and Thiele, 2015). On the other hand, we find that syndicates of venture capitalists and corporate venture capitalists decrease start-ups' survival chances. This configuration might be detrimental for start-ups because both types of equity investors aim to fulfill their financial or strategic goals (Rosenbusch et al., 2013; Yang et al., 2014). While venture capitalists aim to squeeze the start-ups financially corporate venture capitalists aim to benefit from start-ups for their own success. Therefore, the combination of venture capitalists and corporate venture capitalists implies the danger that these two equity investors act as locusts and just leave behind a skeleton of a start-up.

2.5.2 Implications for Theory

This study offers several contributions to research. First, prior research investigating the role of equity investors either focuses on the influence of one, or at most of two, equity investors on start-up performance (see Table 2.1). From these insights, scholars developed a general understanding of the application of a pecking order in entrepreneurial finance, claiming to focus first on business angels, then corporate venture capitalists, and finally venture capitalists for seeking investments (e.g., Block et al., 2018a; Paul et al., 2007a). However, this conventional wisdom is empirically uncontested yet. We close this research gap and empirically show if and under which conditions different types of equity investors are beneficial for start-ups in terms of survival chances.

Second, extant studies that examine equity investors' impact on start-ups mainly consider samples of active start-ups. Hence, studies suffer from survival bias because they exclude failed start-ups (Manigart et al., 2002; Rosenbusch et al., 2013). By analyzing a sample of closed and active start-ups, we avoid survival bias and are able to derive implications that are more viable. In fact, our results reveal that previous studies must be taken with caution because results do not hold when we also consider closed start-ups. Different to research looking at performance or growth of active start-ups (e.g., Bertoni et al., 2011; Stubner et al., 2007), we do not confirm venture capitalists' often acknowledged positive impact on their investees when we examine start-ups' survival chances.

Third, existing research often argues for a positive effect of equity investors on start-up performance or growth (e.g., Bertoni et al., 2011; Kelly and Kim, 2018). However, many studies in this field follow this logic without providing reasoning for the assumed positive effects, i.e. they lack a sound theoretical background. By drawing on agency theory (Jensen and Meckling, 1976), we focus on the goals of different stakeholders and argue that goal congruence is essential for the success of investment relationships (Arthurs and Busenitz, 2003). Furthermore, we extend agency theory in the setting of entrepreneurial finance by introducing start-up age and syndication as two factors, which determine goal congruence between equity investors and start-ups.

Fourth, prior research rarely examines whether the effects of equity investors vary by start-up age. Rosenbusch et al. (2013) provide one of the few insights as they meta-analytically examine the relationship between venture capital investments and start-up performance while considering different age groups of firms. They differentiate between start-ups, growth-stage firms, and mature firms, thus finding that the positive impact of venture capitalists is less relevant for start-ups (Rosenbusch et al., 2013). Going beyond this study, we focus on start-ups and delve deeper into examining the first ten years of start-ups' existence. Therefore, we are able to show exactly when specific equity investors become beneficial or detrimental. Additionally, we extend current knowledge by revealing that start-up age also affects business angels' and corporate venture capitalists' influence on start-up survival, which empirical research has neglected so far.

Finally, we contribute to research by analyzing investor syndication as factor influencing start-up survival. Most studies concentrate on syndication among venture capitalists (e.g., Brander et al., 2002; Dimov and De Clercq, 2006). We go beyond these studies because we analyze syndication among different types of equity investors. In this regard, we find that the value-added hypothesis of investor syndication is not only true for venture capital syndicates

(Brander et al., 2002). In general, we show that syndicated investments among different types of investors increase start-ups survival. Going beyond this direct effect, we demonstrate that the effect of syndicates on start-up survival depends on the configuration of syndicates. While one form of syndication is beneficial and another one is detrimental for start-ups' survival chances, two syndicate configurations turn out to be irrelevant for start-ups' survival chances. For example, our study suggests that co-investments of business angels and venture capitalists not only drive start-up performance (Croce et al., 2018) but also increases survival chances of start-ups.

2.5.3 Implications for Practice

This study provides valuable insights for start-ups that are searching for external investments. We advise these start-ups to evaluate their acquisition strategy of external investments thoroughly, i.e. which type(s) of equity investor(s) to attract. In fact, start-ups' shortsighted strategy to close their funding gap by getting money from wherever possible can backfire in the long term. In general, start-ups should ponder to attract venture capitalists or corporate venture capitalists as they decrease start-ups' survival chances. In contrast, start-ups should focus on attracting business angels because they increase the probability of survival. To convince business angels, start-ups should highlight their commitment and passion (Conti et al., 2013b; Hsu et al., 2014). Start-ups can signal their commitment and passion through acquiring founder, friends, and family money before attracting business angels (Conti et al., 2013b).

Furthermore, when start-ups decide to attract specific equity investors, they need to account for their own age. Young start-ups can select their equity investors relatively riskless because business angels and venture capitalists do not affect survival chances in the early years while acquiring corporate venture capital makes most sense for young start-ups. In this regard, young start-ups should make sure that there is a strategic fit with a potential corporate venture capitalist because such investment relationships become most successful (Ivanov and Xie, 2010). However, while start-ups grow up, they have to adjust their acquisition strategy because corporate venture capitalists and venture capitalists turn out to be risky investors in the later years. Therefore, grown-up start-ups should especially concentrate on attracting business angels.

In their choice of investors, start-ups can also consider syndicates of different types of equity investors because different types of investors can provide complementary resources. Nevertheless, start-ups should select syndicates carefully because specific configurations of syndicates decrease survival chances. While start-ups should refrain from a syndicate of venture capitalists and corporate venture capitalists, a syndicate of business angels and venture capitalists is beneficial for start-ups. Thus, when receiving an investment from venture capitalists, start-ups should strive for business angels as additional investors to increase survival chances. To attract such syndicates, start-ups should send human capital signals because both business angels and venture capitalists are attracted by such signals (Hsu et al., 2014).

Our findings also provide several implications for equity investors. First, business angels should invest in start-ups that are at least two years old. In this context, our results suggest that business angels should concentrate on providing their general business expertise because this is their core competency (Macht and Robinson, 2009). Business angels should also support their investees to acquire additional financing from venture capitalists. Second, contrary to the developments of the venture capital industry towards later-stage investments (Gompers, 1995; Hellmann and Thiele, 2015), we advise venture capitalists to invest in very young start-ups. Furthermore, venture capitalists should encourage their investees to attract business angels as additional investors and make their investees aware of the risks of corporate venture capitalists as additional investors. Third, we advise corporate venture capitalists to emphasize early-stage investments if they aim at supporting their investees in the long term. In these situations, corporate venture capitalists should avoid investing in start-ups that already received an investment from venture capitalists. If corporate venture capitalists rather aim at absorbing knowledge from the start-up in the short-term, later-stage and syndicated investments are still attractive for them.

2.5.4 Limitations and Future Research

This study has some limitations that open up avenues for future research. Drawing on agency theory (Jensen and Meckling, 1976) and proposing that goal (in)congruence results in (in)effective relationships, we have established the impact of different types of equity investors on the probability of start-ups' survival chances. However, we are unable to show how (in)congruent goals result in (in)effective relationships. In other words, we are unable to disentangle which exact kind of activities explain equity investors' effects on start-ups' developments (e.g., Sapienza, 1992). Future research needs to delve deeper into these mechanisms and examine whether activities change when goals are (in)congruent and how this affects start-ups' survival chances.

Another limitation refers to the underlying database. Even though Crunchbase is a precise and reliable data source (e.g., Chatterji et al., 2019; Marx and Fuegi, 2020), it does not provide information regarding the duration of investments. Hence, we can provide insights on syndication across the start-up lifecycle but we cannot differentiate if syndication took place at the same time or sequentially. Despite this drawback, we relied on data from Crunchbase because it contains data on active and closed start-ups, which allowed us to overcome survival bias. Nevertheless, future research should replicate our approach but consider the syndication aspect by differentiating co-investments at the same time and sequential investments by equity investors (Croce et al., 2018).

2.5.5 Conclusion

Prior research, that concentrates on the impact of equity investors, focuses on how the performance or growth among active start-ups varies depending on the involvement of equity investors (e.g., Bertoni et al., 2011; Stubner et al., 2007). These studies derive implications for start-ups in terms of which equity investors to pursue to perform better. However, in this manuscript, we turned to the first priority of start-ups, i.e. to survive, and argued that goals of equity investors and start-ups are more or less congruent depending on the type of equity investor. In this regard, incongruent goals can impede start-ups’ survival chances. Following this approach allowed us to derive implications for start-ups in terms of which equity investors to pursue to survive more likely. Thus, this study differentiates itself from prior research by shifting the focus from start-up performance and growth to survival.

3 The Regional Context in Venture Capital Investments: A Longitudinal Multilevel Study of High-tech Start-ups (Study 2)

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Abstract

By drawing on context effects theory, we develop that a region's geographical accessibility and knowledge stock influence how venture capitalists evaluate a start-up's knowledge stock when making investment decisions. A multilevel model examining 180,952 observations of 46,379 high-tech start-ups located in 402 German regions confirms these predictions. Specifically, we find that a region's geographical accessibility (knowledge stock) strengthens (weakens) the relationship between a start-up's knowledge stock and obtained venture capital investments. This study adds knowledge by demonstrating the relevance of the regional context in venture capital investments.

Keywords

Venture capital; Regional development; Knowledge stock; Geographical accessibility; Multilevel analysis

Status

Working Paper

3.1 Introduction

Around the world, hubs of entrepreneurship emerged and are still emerging. Currently, there are established hubs such as the Silicon Valley but also more recent hubs such as Tel Aviv or Mumbai. We also see several areas that aim to become entrepreneurship hubs such as Reykjavik or Bangkok. Such entrepreneurship hubs are usually very knowledge-intensive and easily accessible (Adams, 2020; Kenney and Von Burg, 1999), and thus attract venture capitalists who invest in start-ups located in such hubs. Due to the resulting potential of entrepreneurship hubs to potentially increase the probability for start-ups to close their funding gaps, it might be strategically interesting for start-ups to locate in such hubs. In contrast, a resulting overload of start-ups in such entrepreneurship hubs might lead to a reduced probability of financing. Hence, this study addresses whether it is beneficial for start-ups to move to an entrepreneurship hub or rather avoid them when seeking venture capital investments.

Venture capitalists are very selective when investing in start-ups (Drover et al., 2017a). They dedicate time and resources to screen start-ups prior to an investment (Maier and Walker, 1987; Muzyka et al., 1996). In turn, start-ups have to convince venture capitalists of their investment worthiness. In this regard, research reveals that start-ups can send signals to venture capitalists to show their investment worthiness. Extant studies show that a start-up's knowledge stock is one of the most important signals of investment worthiness that start-ups can send (e.g., Mann and Sager, 2007; Wu and Shanley, 2009). In general, a start-up's knowledge stock refers to the aggregated knowledge elements, such as patents, within the start-up, i.e. the knowledge stock reflects the amount of a firm's knowledge (Dierickx and Cool, 1989). In this regard, we concentrate on the newly created knowledge stock because this new knowledge is especially interesting for venture capitalists as it is usually not commercialized yet and provides the basis for entrepreneurial opportunities (Audretsch and Lehmann, 2005). We argue that the need to signal the newly created knowledge stock to venture capitalists is especially given for high-tech start-ups due to their knowledge-intensive nature (Zaheer et al., 2010). However, knowledge is intangible (Berman et al., 2002) and start-ups have to reveal more observable information to signal their knowledge stock to venture capitalists. In fact, most studies focus on the number of a start-up's patents (e.g., Lahr and Mina, 2016; Mann and Sager, 2007). Research demonstrates that a start-up's knowledge stock increases the likelihood of receiving venture capital (e.g., Haeussler et al., 2014; Lahr and Mina, 2016), the invested amount of venture capital (e.g., Baum and Silverman, 2004; Zhou et al., 2016), and the number of venture capital investments (e.g., Mann and Sager, 2007). This established impact of a start-up's newly created knowledge stock on receiving venture capital investments provides the basis for this study.

However, we argue that it is not sufficient to examine this relationship solely on the start-up level. This is in line with Colombo's (2021) comprehensive review on signaling in entrepreneurial finance, in which he emphasizes the relevance of contextual factors when analyzing the effectiveness of signals. However, existing research only concentrates on factors on the level of the firm or the entrepreneurs (Colombo, 2021). In this vein, context effects theory postulates that context information influences the evaluation of a target object (Meyers-Levy et al., 2010; Whetten, 2009), i.e. context information determines how venture capitalists evaluate a start-up. Going beyond existing research, we expect that regional context effects are of utmost importance for understanding how a start-up can strengthen its newly created knowledge stock's impact on venture capital investments, and thus convince venture capitalists of their investment worthiness.

Specifically, we argue that there are three reasons why the regional context should matter: First, research regards entrepreneurship as a regional phenomenon (e.g., Fritsch and Wyrwich, 2014; Konon et al., 2018) because start-ups congregate and interact within their regional ecosystems (Pe'er and Keil, 2013). Second, knowledge is also a regional phenomenon (e.g., Asheim and Coenen, 2005; Jaffe et al., 1993) because knowledge transfers usually take place within regional boundaries (e.g., Audretsch and Lehmann, 2005; Jaffe et al., 1993). Third, even though venture capitalists state that they do not favor specific regions over other regions (Martin et al., 2005), venture capital investments exhibit a regional component as venture capitalists usually spread their investments unequally across regions (e.g., Cheng et al., 2019; Lutz et al., 2013). This insight implies that the regional context has an unconscious effect on venture capitalists. For instance, the Bay Area and the Boston-New York-Washington corridor account for 48% of all venture capital investments in the United States (Florida and Mellander, 2016).

Although researchers argue that there is a regional component in venture capital financing (e.g., Florida and Mellander, 2016; Lutz et al., 2013), existing studies do not account for the regional context sufficiently to explain this regional component. Specifically, studies do not examine the interplay of start-ups' characteristics and regional characteristics as most studies examine venture capital investments by referring to either start-up characteristics (e.g., Baum and Silverman, 2004; Zhou et al., 2016) or regional characteristics (e.g., Florida and Mellander, 2016; Lutz et al., 2013). Therefore, the aim of this study is to examine the interplay of the individual (i.e., start-up) and regional level in venture capital investments. Thus, we respond to the call for multilevel research on venture capitalists' decisions for start-up investments (Shepherd, 2011). To reach this aim, we argue that two regional components, i.e. a region's newly created knowledge stock and a region's geographical accessibility, influence the relationship between a start-up's newly created knowledge stock and venture capital investments in the respective start-up. We concentrate on these two specific regional factors because existing studies find that a region's knowledge stock and geographical accessibility correlate with venture capital investments (e.g., Florida and Mellander, 2016; Masiak et al., 2020). Analogously to a firm's knowledge stock, the region's knowledge stock refers to the aggregated knowledge elements, which are newly created by all firms located in one region (cf. Dierickx and Cool, 1989). A region's geographical accessibility refers to the convenience with which venture capitalists can reach regions and economic actors within these regions (cf. Apparicio et al., 2008). Hence, geographical accessibility reflects how easily venture capitalists and start-ups can interact with each other. Consequently, we formulate the following research question: *Do a region's newly created knowledge stock and geographical accessibility influence the effectiveness of a start-up's newly created knowledge stock to attract venture capital investments?*

This study contributes to research in several ways. First, existing research reveals that start-ups can signal their investment worthiness via their newly created knowledge stock (e.g., Hsu and Ziedonis, 2013; Mann and Sager, 2007). By following a multilevel approach, we extend this knowledge by demonstrating that regional factors can alter this signaling effect of a start-up's knowledge stock. Second, context effects theory is usually applied in consumer research (e.g., Laczniak and Teas, 2002; Meyers-Levy et al., 2010). We are the first to introduce this theory to the research setting of start-up financing since most existing studies apply signaling theory to derive context effects on the individual level (e.g., Haeussler et al., 2014; Hoenen et al., 2014). Therefore, we are the first to shed light on the relevance of regional context effects for venture capitalists' individual investment decisions. Third, extant research indicates that venture capitalists spread their investments unequally across regions (e.g., Florida and Mellander, 2016; Lutz et al., 2013). However, so far, research cannot explain if this regional component affects venture capital investment on the individual level. We empirically test this and reveal that regional factors determine venture capitalists' investments decisions on the individual level, which explains the regional distribution of venture capital investments.

3.2 Theory and Hypotheses

3.2.1 Context Effects Theory

Context effects theory addresses the question of which contextual effects explain varying organization practices (Whetten, 2009). In other words, the key statement of context effects theory is that contextual information can influence the evaluation of a target object (Meyers-

Levy et al., 2010), which comprises two stages: encoding and judgement (Schwarz and Bless, 2007). The influence of contextual information can take place during both stages of target object evaluation (Schwarz and Bless, 2007). First, the encoding stage refers to the phase when the initial interpretation of the target object takes place (Meyers-Levy et al., 2010). During this stage, context information serves as an interpretive frame, which helps people to understand the target object and gives people a first impression of the target object (Meyers-Levy et al., 2010). Second, the judgement stage refers to the phase when people compare the target object with a pertinent standard (Schwarz and Bless, 2007), which is derived from context information (Meyers-Levy et al., 2010). Therefore, people formally evaluate the target object in this stage (Schwarz and Bless, 2007).

Context effects theory accounts for two types of context effects depending on the direction of contextual influences: assimilation and contrast effects. On the one hand, assimilation effects refer to positive correlations between judgements and the valence of context information; i.e., positive (negative) contextual information lead to more positive (negative) evaluations (Meyers-Levy et al., 2010; Schwarz and Bless, 2007). Such assimilation effects arise when the decision maker creates new information about the target object in her mind based on the contextual information she gained (Schwarz and Bless, 2007). On the other hand, contrast effects refer to situations when there is a negative correlation between judgements and the valence of context information; i.e., positive (negative) contextual information lead to more negative (positive) valuations (Schwarz and Bless, 2007). Contrast effects arise when contextual information set a certain standard or scale anchor to judge the target object (Schwarz and Bless, 2007). Schwarz and Bless (2007) explain these two effects with an example from politics. Assimilation effects arise when an untrustworthy politician, such as Richard Nixon, negatively affects politicians’ trustworthiness in general. However, this untrustworthy politician increases the trustworthiness of any other specific politician so that contrast effects emerge.

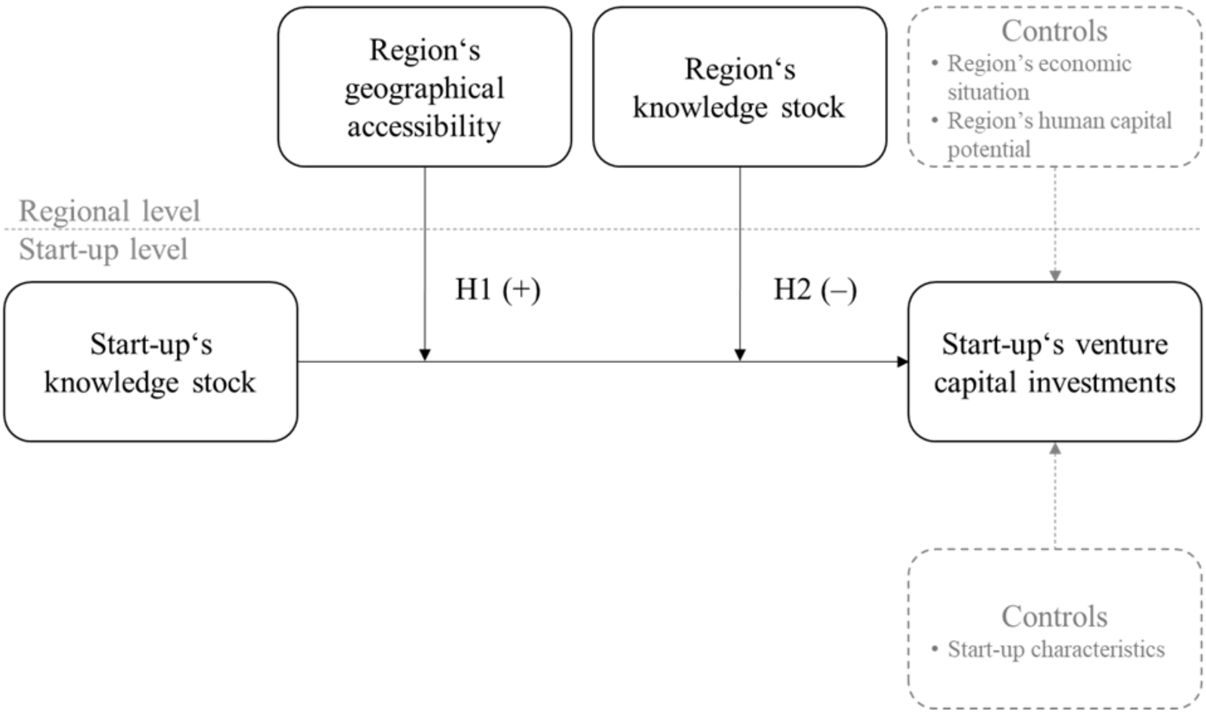
In this study, we apply context effects theory to venture capital financing. In venture capital financing, venture capitalists serve as organizations, whose evaluation of a high-tech start-up, i.e. the target object, should vary in different contexts. In venture capital financing, the encoding stage encompasses the initial contact between venture capitalists and start-ups, when venture capitalists interpret information about potential investees. In the judgement stage, venture capitalists draw conclusion from the context, e.g., the collected information about certain standards among start-ups and compare start-ups. These activities in the encoding and judgement stage can result in contrast or assimilation effects, which we hypothesize in the following chapter.

3.2.2 Context Effects in Venture Capital Financing

As foundation for our reasoning, we draw on the established impact of a start-up's knowledge stock on receiving venture capital investments. As knowledge is intangible (Berman et al., 2002), most studies examine start-ups' patents as more observable signal of knowledge (e.g., Lahr and Mina, 2016; Mann and Sager, 2007). In fact, patents allow start-ups to codify their newly created knowledge (Bonaccorsi et al., 2014) so that patent applications reflect the start-up's newly created knowledge stock (Ahuja and Katila, 2001). Most existing studies draw on signaling theory to explain the attractive power of patents, i.e. the newly created knowledge stock, in venture capital financing (e.g., Haeussler et al., 2014; Hsu and Ziedonis, 2013). For instance, Mann and Sager (2007) observe software start-ups and find that both the existence of any patent and the number of patents increases the number of financing rounds and total investments by venture capitalists.

However, following the logic of context effects theory (Whetten, 2009), we argue that the regional context affects this relationship between a start-up's newly created knowledge stock and venture capital investments. First, we argue that a region's geographical accessibility leads to assimilation effects. Second, we propose that a region's newly created knowledge stock results in contrast effects. Figure 3.1 illustrates this study's conceptual model.

Figure 3.1: Conceptual Model (Study 2)



3.2.2.1 The Moderating Role of the Region's Geographical Accessibility

We propose that a region's geographical accessibility affects the effect of a start-up's newly created knowledge stock on venture capital investments. Geographical accessibility should be a relevant factor in this context because we argue that it allows a stronger direct involvement of venture capitalists so that returns on investments should become greater.

Venture capitalists invest in start-ups because they expect substantial returns on their high-risk investments (Carpenter and Petersen, 2002). In this regard, start-ups that possess a broad newly created knowledge stock are more attractive for venture capitalists because such start-ups are more likely to generate higher returns on investments as a start-up's newly created knowledge stock is a driver of innovation performance (Wu and Shanley, 2009). Moreover, venture capitalists can contribute to a start-up's development even further than providing financial resources. Since venture capitalists are active investors, they can also provide value-adding activities such as mentoring and advising (Bacon-Gerasymenko and Eggers, 2019; Sapienza et al., 1996), which aim at increasing start-up's performance and success chances (Proksch et al., 2017). For instance, venture capitalists can help start-ups commercialize their knowledge stocks (Samila and Sorenson, 2010) as this new knowledge is usually not commercialized yet. Thus, venture capitalists can especially use this uncommercialized knowledge to contribute to their investee's development. Research further reveals that value-adding activities are most effective when start-ups are already performing well (Sapienza et al., 1996), which is usually the case when they possess a broad knowledge stock (Wu and Shanley, 2009). Hence, venture capitalists' value-adding activities should be especially effective when start-ups possess a broad newly created knowledge stock.

To allow effective value-adding activities by venture capitalists, start-ups need to be geographically accessible because value-adding activities require frequent personal contacts between venture capitalists and their investees (Cumming and Dai, 2010; Florida and Kenney, 1988). Instead, geographical inaccessibility impedes such contacts so that venture capitalists' activities become less effective and efficient (Lerner, 1995; Sorenson and Stuart, 2001). These disadvantages arise, for example, due to higher expenses in terms of time and money to support start-ups located in geographical inaccessible regions (Fritsch and Schilder, 2008; Lutz et al., 2013). In contrast, greater geographical accessibility should allow easier contact for and stronger involvement of venture capitalists. For instance, face-to-face interactions between venture capitalists and their investees are more likely when geographical accessibility is high, which will lead to more successful relationships (cf. McPherson et al., 2001).

Based on this knowledge, which venture capitalists are also aware of, we argue that a start-up's newly created knowledge stock should become more attractive from the perspective of venture capitalists when the start-up is located in a geographically accessible region. In this case, start-ups possess the necessary assets (i.e., knowledge), which venture capitalists can help transform into performance by providing value-adding activities more efficiently and effectively due to greater geographical accessibility. In line with context effects theory, a region's geographical accessibility provides context information that serves as an interpretive frame that helps investors to evaluate the potential investee (cf. Meyers-Levy et al., 2010). By this means, an investor's positive evaluation of a start-up's newly created knowledge stock should become more positive when the region is geographically accessible. In other words, investors should know that a better (worse) geographical accessibility allows (hinders) them to enhance the commercialization of their investee's newly created knowledge stock so that the start-up's success chances increases (decreases). Thus, assimilation effects emerge as venture capitalists create new information about the target object in their mind based on the contextual information they gained (Meyers-Levy et al., 2010; Schwarz and Bless, 2007). Venture capitalists should anticipate these effects and prefer investing in start-ups, which have a broad newly created knowledge stock, when these start-ups reside in geographically accessible regions. As a result, such start-ups should acquire more venture capital investments. We hypothesize:

> *Hypothesis 1: The region's geographical accessibility moderates the relationship between a start-up's newly created knowledge stock and venture capital investments; in such a way, that a greater (smaller) region's geographical accessibility strengthens (weakens) the positive effect of a start-up's newly created knowledge stock on received venture capital investments.*

3.2.2.2 The Moderating Role of the Region's Knowledge Stock

Additionally, we argue that a region's newly created knowledge stock can be harmful or supportive for start-ups' chances to convince venture capitalists for investments. Following context effects theory (Schwarz and Bless, 2007), we argue that context information on a region's newly created knowledge stock serves as a reference standard for venture capitalists.

When venture capitalists judge a start-up's investment worthiness, they gather additional information (Fried and Hisrich, 1994). In this regard, venture capitalists often turn to outside sources of information and compare this information with their initial information about the start-up (Fried and Hisrich, 1994). A region's newly created knowledge stock can act as such an outside source of information, thus providing evidence about the standard among comparable start-ups. In fact, this regional frame of reference should be relevant for venture capitalists because venture capitalists often concentrate on specific regions when spreading their investments (e.g., Coval and Moskowitz, 1999; Samila and Sorenson, 2010). Hence, venture capitalists know the regional context and are able judge the region's newly created knowledge stock. Then, venture capitalists compare the individual start-up's newly created knowledge stock with the region's newly created knowledge stock to judge the start-up's investment worthiness. This comparison takes place in the judgement stage as investors compare the target object with a pertinent standard (Schwarz and Bless, 2007).

When a region's newly created knowledge stock is small, a start-up's newly created knowledge stock should signal a greater investment worthiness for venture capitalists because this start-up exceeds the regional standard; that is, contrast effects emerge (Schwarz and Bless, 2007). Analogously, when a region's newly created knowledge stock is greater, a start-up's newly created knowledge stock should be less attractive from the perspective of venture capitalists because this individual start-up appears less knowledge-intensive than comparable start-ups, and thus less investment worthy. For instance, Munich and its surroundings is among Germany's most knowledge-intensive regions (German Patent and Trade Mark Office, 2019). In this region, venture capitalists might evaluate start-ups who applied for one patent as below average in terms of their newly created knowledge stock because the region is very knowledge-intensive. However, venture capitalists would evaluate the same start-up's newly created knowledge stock as above average if the start-up was located in Bremen, where the region's knowledge stock is relatively small (German Patent and Trade Mark Office, 2019).

Overall, we argue that the region's newly created knowledge stock sets a standard for start-ups located in that region, which affects venture capitalists' decisions. In knowledge-intensive regions, start-up's newly created knowledge stock becomes less attractive because start-ups cannot differentiate themselves from other start-ups in that region. In less knowledge-intensive regions, however, start-ups stand out when they possess a broad newly created knowledge stock. As a result, these start-ups should signal a greater investment worthiness, leading to more venture capital investments. Hence, we hypothesize:

> *Hypothesis 2: The region's newly created knowledge stock moderates the relationship between a start-up's newly created knowledge stock and venture capital investments; in such a way, that a greater (smaller) region's newly created knowledge stock weakens (strengthens) the positive effect of a start-up's newly created knowledge stock on received venture capital investments.*

3.3 Methodology

3.3.1 Sample and Data Sources

To test our hypotheses, we collected data from several sources. The Spotfolio database provided the basis for our sample. Spotfolio is a German search and matching platform, which includes information on German high-tech firms including patent, trademark, and funding data (Spotfolio GmbH, 2015). Spotfolio focuses on high-tech firms who operate in a research-intensive industry or provide a technology-oriented offering (Heger et al., 2011). In this regard, the database covers listed high-tech companies as well as small- and medium-sized high-tech firms (Spotfolio GmbH, 2015). Spotfolio uses data from the Federal Gazette and extends it with data from additional sources (Spotfolio GmbH, 2015). For instance, Spotfolio crawls the firms' websites to gather and update their database. Additionally, Spotfolio draws on self-reported data provided by the firms.

We used the Spotfolio database as of December 2016, which contains 95,357 German high-tech firms of every age. Due to data availability limitations within this database, we can include all firms founded on or before 2014/12/31, resulting in 82,807 firms. We then excluded all firms that were older than 10 years as of 2014/12/31 because our aim is to analyze start-ups. Thus, we followed the approach taken by several previous studies to identify start-ups (e.g., Baum and Silverman, 2004); this resulted in a reduced sample of 47,995 start-ups. Zip codes, the essential information to match start-ups to regions, were missing for 2,332 cases. For these missing cases, we collected zip codes by hand and were able to add them for 723 start-ups. However, we had to exclude the remaining firms without zip codes (1,609 cases). Finally, we excluded seven foreign firms from the sample. Thus, our sample consists of 46,379 German high-tech start-ups. For each of these start-ups, we were able to collect and compute observations across years, which leads to a longitudinal sample that encompasses 180,952 observations. Depending on the foundation year of the start-ups, each start-up has observations from one up to ten years.

In the next step, we collected data on the regional level to create a multilevel database consisting of data on the start-up and regional level. Germany consists of 402 German regions, which include both districts ("Kreise") and autonomous cities ("kreisfreie Städte"). This list serves as basis for the compilation of the database on the regional level. Examining these 402 districts and autonomous cities is a very common approach to analyze German data on the regional level (e.g., Brixy et al., 2020). Referring to the regions allows us to find regional differences. We complemented this list of German regions with data from four additional sources: (1) Indicators, Maps and Graphics on Spatial and Urban Monitoring (INKAR), (2) Regional Database Germany, (3) Higher Education Compass, and (4) PCT Patent Database. First, the Federal Office for Building and Regional Planning (BBSR) provides the database INKAR (BBSR, 2016b). This interactive online atlas illustrates living conditions and allows comparing German regions across a variety of topics, such as education and economic factors (BBSR, 2016b). Second, the Regional Database Germany is a database provided by the German Federal Statistical Office (Destatis). This database includes various official statistics on the regional level, such as the region's size (Destatis, 2017). Third, the German Rectors Conference provides the Higher Education Compass, which contains data regarding both public and state-approved universities. The compass further provides an overview of several characteristics, such as the universities' locations (German Rectors' Conference, 2016). Fourth, the World Intellectual Property Organization (WIPO) provides the PCT Patent Database, which includes data on filed patents, such as year of a patent filed and regional origin of a patent (WIPO, 2018). From this database, we considered 184.648 patents filed in Germany from 2005 until 2014 and aggregated them to the 402 regions.

3.3.2 Variables

Table 3.1 provides an overview on all variables and corresponding data sources.

3.3.2.1 Dependent Variable (Start-up Level)

From the Spotfolio database, we know how often and when a start-up received venture capital investments. We used this information to determine the number of venture capital investments (i.e., funding rounds) a start-up received in each year and labeled the variable as *number of venture capital investments*. Thus, we followed similar approaches to measure venture capital investments in start-ups (e.g., Conti et al., 2013a; Mann and Sager, 2007). Due to skewness, we logarithmized this variable.

3.3.2.2 Independent Variable (Start-up Level)

In practice, start-ups have to signal their newly created knowledge stock to venture capitalists because knowledge is intangible (Ndofor and Levitas, 2004). Start-ups accomplish this by applying for patents and revealing their patent portfolio to investors (Ahuja and Katila, 2001). Hence, we measured a start-up's newly created knowledge stock via the number of patents applied for in the corresponding year and labeled the variable as *firm patents*. We follow several studies examining patents to reflect a start-up's newly created knowledge stock and how these patents determine fundraising success (e.g., Khoury et al., 2015; Mann and Sager, 2007). Due to skewness, we logarithmized this variable.

Table 3.1: Description of Variables (Study 2)

Construct	Variable	Explanation	Data source
Dependent Variable (Start-up Level)			
Start-up's Venture Capital Investments	*Number of Venture Capital Investments (log)*	The number of venture capital investments in one start-up. Due to skewness, we logarithmized this variable. We calculated this variable for each year from 2005 to 2014 the corresponding start-up was active.	Spotfolio
Independent Variables (Start-up Level)			
Start-up's Newly Created Knowledge Stock	*Firm Patents (log)*	The number of patents applied for by a start-up. Due to skewness, we logarithmized this variable. We calculated this variable for each year from 2005 to 2014 the corresponding start-up was active.	PCT Patent Database
Independent Variables (Regional Level)			
Region's Geographical Accessibility	*Population Density*	The number of inhabitants located in a region in relation to the size of this region (in km²). We collected this variable for each year from 2005 to 2014.	INKAR
Region's Newly Created Knowledge Stock	*Patent Density*	The number of patents applied for by all firms in a region in relation to the size of this region (in km²). We calculated this variable for each year from 2005 to 2014.	PCT Patent Database & Destatis
Control Variables (Start-up Level)			
Start-up Characteristics	*Firm Size*	A categorical variable consisting of five groups depending on the start-up's number of employees. We calculated this variable for each year from 2005 to 2014.	Spotfolio
Start-up Characteristics	*Firm Age*	The number of years a start-up has been operating since its foundation. We calculated this variable for each year from 2005 to 2014.	Spotfolio
Control Variables (Regional Level)			
Region's Economic Situation	*Household Income*	The average household income of a region per inhabitant (in €). We collected this variable for each year from 2005 to 2014.	INKAR
Region's Economic Situation	*GDP*	The gross domestic product of a region per inhabitant (in 1,000 €). We collected this variable for each year from 2005 to 2014.	INKAR
Region's Human Capital Potential	*Unemployment*	The number of unemployed persons in a region per 1,000 inhabitants in the working age population. We collected this variable for each year from 2005 to 2014.	INKAR

3.3.2.3 Independent Variables (Regional Level)

On the regional level, we examine two constructs: a region's newly created knowledge stock and a region's geographical accessibility. First, we accounted for a region's geographical accessibility through the variable *population density*. Densely-populated regions are usually more accessible than rural regions because means of transportation are better developed (Song et al., 2012). To reflect densely populated regions, we included the variable population density, which measures the number of inhabitants located in a region in relation to the region's size for each year. This is an appropriate measure as regions are usually defined as densely populated regions or rural regions via their population density. Moreover, we know that population density and infrastructure's development correlate (Glover and Simon, 1975).

Second, in terms of a region's newly created knowledge stock, we operationalized the variable *patent density*. Patent density accounts for the number of patents applied for by all firms in one region in the corresponding year in relation to the size of this region (in km²). Thus, we adapted the typical approach to examine patents as proxy for newly created knowledge stock to the regional context (e.g., Acs et al., 2002; Colombelli and Quatraro, 2018), which should be a viable approach because knowledge is a regional phenomenon (e.g., Asheim and Coenen, 2005; Jaffe et al., 1993). Existing studies follow similar approaches by examining patents on the regional level (e.g., Konon et al., 2018; Masiak et al., 2020).

3.3.2.4 Control Variables (Start-up Level)

To account for start-up characteristics, we included two variables on the start-up level: *firm size* and *firm age*. We accounted for these two variables because research has shown that start-up age and start-up size determine start-ups' chances to obtain venture capital (e.g., Bertoni et al., 2015). We take *firm size* a categorical variable consisting of five groups depending on the start-up's number of employees. *Firm age* refers to the number of years a start-up has been operating since its foundation. We calculated both variables for each year from 2005 to 2014.

3.3.2.5 Control Variables (Regional Level)

Following context effects theory, we also included control variables on the regional level, which reflect the region's economic situation and human capital potential. Previous studies show that the economic situation influences venture capitalists' activities (e.g., Félix et al., 2013). To account for this economic situation, we included two control variables that we collected for each year from 2005 to 2014: *household income* and *GDP*. The variable *household income* refers to a region's average household income in € per inhabitant (BBSR, 2016a). The variable *GDP* refers to the gross domestic product of a region per inhabitant (BBSR, 2016a). Further, research reveals that human capital drives venture capital investments (e.g., Kirsch et al., 2009; Ko and McKelvie, 2018). To account for the human capital influence, we analyzed the variable *unemployment*, which we measured as the number of unemployed persons in a region per 1,000 inhabitants in the working age population (BBSR, 2016a). Unemployed people usually exhibit a lower degree of education, i.e. a lower degree of human capital (Cairó and Cajner, 2018).

3.3.3 Statistical Analyses

The data in our sample exhibits a hierarchical structure as start-ups (level 1) are nested within regions (level 2). For such nested data, multilevel modeling is a more appropriate approach to examine relationships than more traditional statistical methods, such as ordinary least squares regression (Yang et al., 2019). Multilevel modeling exhibits multiple advantages in this case. First, multilevel modeling allows a systematic analysis of how variables at different levels as well as cross-level interactions affect an outcome variable (Guo and Zhao, 2000). Second, multilevel modeling avoids biased parameter estimates, which may be biased due to clustering of cases (Guo and Zhao, 2000). Third, multilevel modeling corrects standard errors, confidence intervals, and significance tests by accounting for clustering in the data. Traditional regression techniques do not account for this clustering, and thus violate regressions' basic assumption of independence of observations for nested data (Guo and Zhao, 2000).

To account for the nested data in our sample, we ran a multilevel mixed effects linear regression, consisting of fixed effects and the regions as random effects while also accounting for the longitudinal structure of our sample. To test our research model, we applied the *mixed* command in Stata 14 and employed the maximum likelihood as estimation method. We examined three models. Model 1 consists of all control variables as well as the random effects. In Model 2, we add the direct effects of start-up's newly created knowledge stock, region's geographical accessibility, and region's newly created knowledge stock variables. Model 3 further contains the cross-level interactions, which are essential for testing our hypotheses.

3.4 Results

3.4.1 Descriptive Statistics

Table 3.2 contains descriptive statistics and correlations of all variables considered in this study. In terms of descriptive statistics on the start-up level, we find that, on average, start-ups receive far less than one venture capital investment per year (non-logarithmized mean = .003) while also holding less than one patent (non-logarithmized mean = .072). On the regional level, we see that there are over 1,000 inhabitants (mean = 1,424.771) per km² located in a region. Further, we observe that the average patent density amounts to almost one patent per km² (mean = .939). Our data further reveals that many regions do not exhibit any new patents applications but there are some patent hotspots such as Munich and Stuttgart.

Table 3.2: Descriptive Statistics and Correlations (Study 2)

N = 180,952	Mean	S.D.	Correlations (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	VIF
Dependent Variable (Start-up Level)												
(1) *Number of Venture Capital Investments (log)*	.002	.038	1.000									
Independent Variables (Start-up Level)												
(2) *Firm Patents (log)*	.017	.172	.011	1.000								1.00
Independent Variables (Regional Level)												
(3) *Population Density*	1,424.771	1,380.550	.049	–.022	1.000							2.95
(4) *Patent Density*	.939	2.379	.024	–.002	.589	1.000						2.14
Control Variables (Start-up Level)												
(5) *Firm Size*	.999	1.188	.014	.017	–.032	–.018	1.000					1.01
(6) *Firm Age*	2.341	2.241	–.009	.021	–.054	–.025	–.074	1.000				1.01
Control Variables (Regional Level)												
(7) *Household Income*	1,670.373	261.385	–.001	–.012	.050	.413	–.002	.060	1.000			2.55
(8) *GDP*	38.267	17.766	.016	–.014	.445	.504	–.017	–.002	.545	1.000		1.88
(9) *Unemployment*	63.295	27.955	.023	–.004	.391	–.012	–.016	–.067	–.666	–.207	1.000	2.78

In terms of correlations (see Table 3.2), we find some high correlations for combinations of the control variables unemployment, GDP, and household income. However, such correlations should not affect coefficients when analyzing a longitudinal database (Fritsch & Changoluisa, 2017). Table 3.2 also shows the VIFs for Model 2. All VIFs score well below five (average VIF = 1.915), which is a common threshold applied in research (e.g., Brauer, Mammen, & Luger, 2017). Thus, multicollinearity should not bias our results.

3.4.2 Main Analyses

In Model 1 (see Table 3.3), we observe that a region's economic situation helps start-ups to raise investments from venture capitalists to some extent. In fact, a region's household income (B = .000, p = .054) and GDP (B = .000, p = .000) increase the number of venture capital investments. Similarly, the region's human capital potential is also important in this regard. Start-ups are able to raise more investments when the region exhibits a greater share of unemployment (B = .000, p = .004).

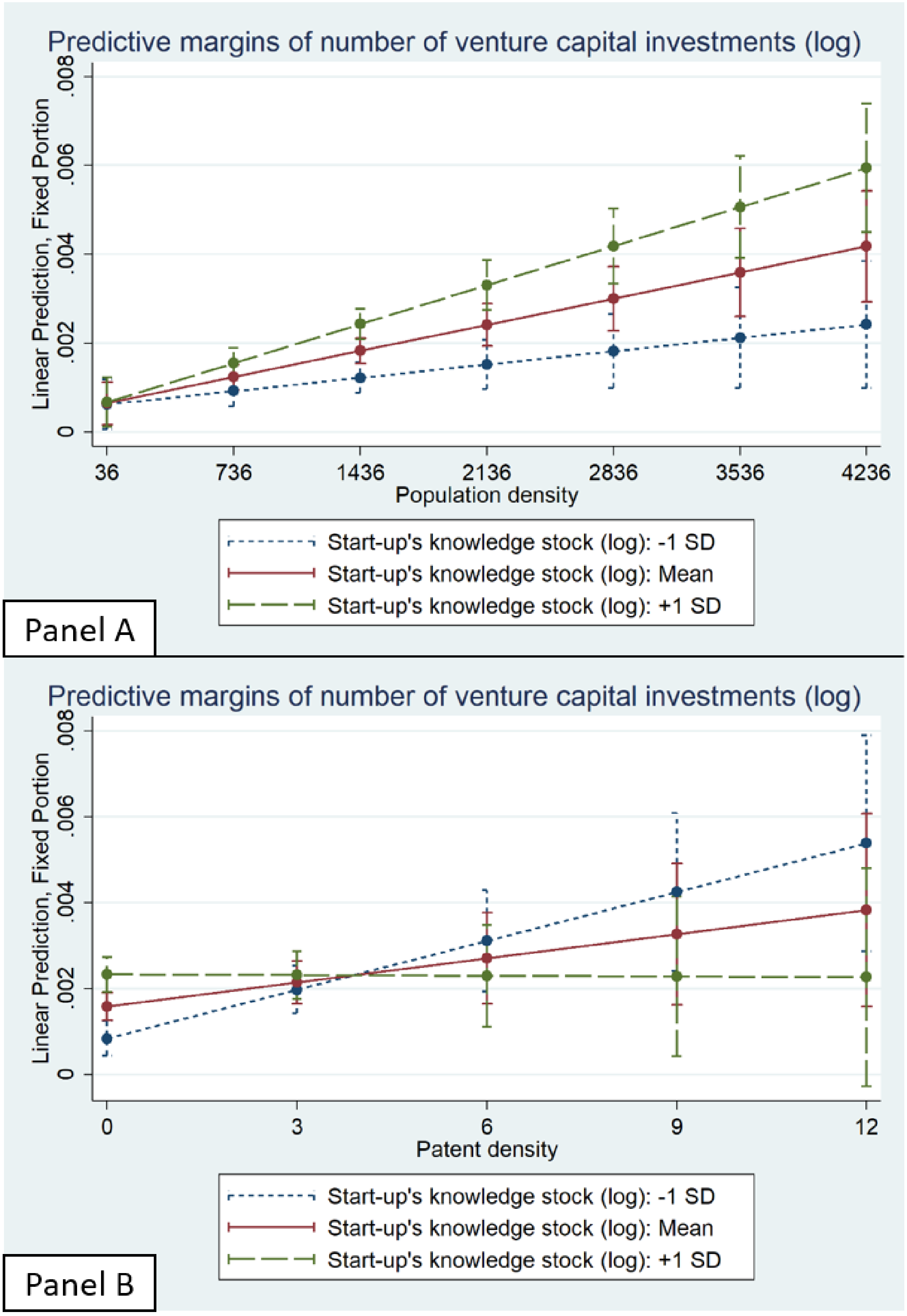
In Model 2 (see Table 3.3), following our fundamental premise, we observe that a start-up's newly created knowledge stock significantly increases the number of venture capital investments (B = .003, p = .000). We further find that a region's geographical accessibility, i.e. population density (B = .000, p = .000), increases the number of venture capital investments a start-up receives. Moreover, the variable patent density, reflecting a region's newly created knowledge stock, increases the number of venture capital investments (B = .000, p = .062).

To test the hypotheses, we ran Model 3 (see Table 3.3). The results reveal that a region's geographical accessibility strengthens the positive impact of a start-up's newly created knowledge stock on the number of venture capital investments. We find a positive moderating effect for population density (B = .000, p = .000). These findings support Hypothesis 1. For population density, Figure 3.2 (Panel A) shows that the effect of a start-up's newly created knowledge stock on the number of venture capital investments is not significant when population density is low. With an increasing population density, owning a broad newly created knowledge stock becomes beneficial for start-ups as they receive more venture capital investments, whereas owning a narrow newly created knowledge stock does not alter the number of venture capital investments across different degrees of population density that much.

Table 3.3: Mixed Effects Linear Regression Results (Study 2)

	Model 1			**Model 2**			**Model 3**		
Dependent variable:	**Number of Venture Capital Investments (log)**			**Number of Venture Capital Investments (log)**			**Number of Venture Capital Investments (log)**		
	B	(S.E., p-value)	[95% CI]	B	(S.E., p-value)	[95% CI]	B	(S.E., p-value)	[95% CI]
Constant	–.00392	(.00139 .005)	[–.00664; –.00120]	–.00209	(.00136 .125)	[–.00476; .00058]	–.00208	(.00136 .127)	[–.00475; .00059]
Control Variables (Start-up Level)									
Firm Size	.00054	(.00009 .000)	[.00037; .00072]	.00054	(.00009 .000)	[.00036; .00071]	.00054	(.00009 .000)	[.00037; .00072]
Firm Age	–.00010	(.00004 .019)	[–.00017; –.00001]	–.00009	(.00004 .020)	[–.00017; .00000]	–.00009	(.00004 .019)	[–.00017; –.00002]
Control Variables (Regional Level)									
Household Income	.00000	(.00000 .054)	[–.00000; .00001]	.00000	(.00000 .125)	[–.00000; .00002]	.00000	(.00000 .122)	[–.00000; .00000]
GDP	.00004	(.00001 .000)	[.00002; .00006]	.00000	(.00001 .880)	[–.00002; .00002]	.00000	(.00001 .868)	[–.00002; .00002]
Unemployment	.00002	(.00001 .004)	[.00001; .00003]	.00000	(.00001 .435)	[–.00001; .00367]	.00001	(.00001 .442)	[–.00001; .00002]
Independent Variables (Start-up Level)									
Firm Patents (log)				.00265	(.00052 .000)	[.00162; .00367]	.00107	(.00075 .151)	[–.00039; .00254]
Independent Variables (Regional Level)									
Population Density				.00000	(.00000 .000)	[.00000; .00000]	.00000	(.00000 .000)	[.00000; .00000]
Patent Density				.00019	(.00010 .062)	[–.00001; .00039]	.00021	(.00010 .046)	[.00000; .00041]
Interactions									
Firm Patents (log) X Population Density							.00000	(.00000 .000)	[.00000; .00000]
Firm Patents (log) X Patent Density							–.00112	(.00032 .000)	[–.00174; –.00049]
Log Likelihood	333,783.68			333,812.38			333,819.70		
Wald Chi ²	81.05 (p-value = .000)			149.32 (p-value = .000)			63.48 (p-value = .000)		
No. of Observations (No. of Regions)	180,952 (402)			180,952 (402)			180,952 (402)		

Figure 3.2: Interaction Plots (Study 2)



Additionally, we find that a region's knowledge stock weakens the positive impact of a start-up's knowledge stock on the number of venture capital investments. As expected, patent density weakens the main relationship (B = –.001, p = .000). This result provides support for Hypothesis 2. For the moderating effect of patent density, Figure 3.2 (Panel B) illustrates that start-ups receive more investments when they own a broad newly created knowledge stock in regions that account for few patents. However, when the patent density in a region increases, the main effect turns around as owning a broad newly created knowledge stock becomes less attractive for start-ups.

3.4.3 Additional Analyses

3.4.3.1 Alternative Dependent Variables

To test the robustness of our results, we re-ran the mixed effects linear regressions while including a one-year, two-year, and three-year forward of the dependent variable. This is a sensible approach because venture capitalists are very selective so that investments may take some time, resulting in a delay between the impacts of independent variables on the dependent variable. Hence, investments might not take place in the same year. With this approach, we are able to analyze the long-term effects of a region's newly created knowledge stock on the number of venture capital investments while reducing endogeneity issues (Konon et al., 2018). Furthermore, using a forward of the dependent variable helps us to reduce simultaneity problems (Baum and Silverman, 2004; Wennberg et al., 2016). In fact, research often considers the relationship between patenting and venture capital investments through the lens of simultaneity problems (e.g., Baum and Silverman, 2004; Conti et al., 2013a).

These robustness checks provide similar results to our main analysis, which are displayed in Table A7 for the one-year forward, in Table A8 for the two-year forward, and in Table A9 for the three-year forward. First, the positive impact of a start-up's newly created knowledge stock on the number of venture capital investments remains highly significant. Second, the direction of the interaction terms in Models 3 of the respective tables in the appendix confirm the main analysis. Overall, the region's geographical accessibility strengthens and the region's newly created knowledge stock weakens the relationship between a start-up's newly created knowledge stock and the number of venture capital investments. However, we also find that the interaction of a start-up's newly created knowledge stock and population density, which was significant in the main analyses, is not robust across all robustness checks as the corresponding interaction effect is significant in t+1 and t+3 but not in t+2.

3.4.3.2 Alternative Independent Variables

As our results for the moderating role of a regional factors provide interesting insights into arising assimilation and contrast effects in venture capital investments, we conducted additional analyses to explore these effects in more detail, and thus examined additional facets of these phenomena.

On the one hand, we conducted robustness checks with alternative variables reflecting a region's geographical accessibility. First, we replaced the variable population density with the variable commuter balance to account for a region's geographical accessibility. Commuter balance measures the difference of inbound commuters and outbound commuters in relation to the number of all employees subject to social insurance contributions (in percent) in a region (BBSR, 2016a). A high commuter balance means that a lot of outsiders enter a region. Table A10 displays the corresponding results of this robustness check. In this regard, we find that there is a significant and positive interaction of a start-up's newly created knowledge stock and commuter balance ($B = .000$, $p = .046$), which lends further support to Hypothesis 1. Second, we examined the venture capital density instead of population density. A region's geographical accessibility should be greater if the regional availability of venture capitalists is larger, simply because they are already located in the region. Following a similar approach by Sorenson and Stuart (2001), we calculated, for each year, the venture capitalist density as the number of venture capitalists located in a region in relation to the size of this region. To do so, we identified the names of 845 venture capitalists listed in the Spotfolio database. We collected the years of foundations as well as zip codes for these venture capitalists' headquarters to assign each of them to the 402 German regions. After eliminating all venture capitalists, who were not located in Germany, the sample contained 583 venture capitalists at 670 locations. The larger number of locations is because some venture capitalists have multiple equally entitled offices. Table A11 showcases the results of these regressions and we observe further support for our main findings. In fact, venture capital density strengthens the relationship between a start-up's newly created knowledge stock and venture capital investments ($B = .100$, $p = .000$), which supports Hypothesis 1 even further.

On the other hand, we conducted robustness checks with alternative variables reflecting a region's newly created knowledge stock. First, we examined regional research and development (R&D) expenditure density instead of patent density. To do so, we obtained data from the SV Wissenschaftsstatistik GmbH (2020) on regional R&D expenditures. Regional R&D expenditures contain all expenditures for R&D in a region, which was conducted by internal research personnel for the companies' own purposes or external commissions. We set this variable in relation to the size of a region (in km^2) to obtain the R&D expenditure density. Table A12 displays the corresponding regression results. Our results show that, in line with our main analysis, regional R&D expenditure density also weakens the relationship between start-up's newly created knowledge stock and venture capital investments ($B = –.000$, $p = .000$), which lends further support to Hypothesis 2. Second, we replaced the variable patent density by the variable regional R&D personnel density, which we also calculated based on data of SV Wissenschaftsstatistik GmbH (2020). They measure regional R&D personnel as the aggregated number of people working in R&D in a respective region, reported in full-time equivalents. We set this number in relation to the size of a region (in km²) to measure the R&D personnel density. As Table A13 shows, we again find a negative moderating effect of R&D personnel on the relationship between a start-up's newly created knowledge stock and venture capital investments ($B = –.000$, $p = .000$). This provides further support for Hypothesis 2.

3.5 Discussion

3.5.1 Key Findings

Research widely agrees that start-ups can attract venture capital investment by signaling their newly created knowledge stock (e.g., Hsu and Ziedonis, 2013; Mann and Sager, 2007). By drawing on a sample of 180,952 observations of 46,379 high-tech start-ups located in 402 German regions, we confirm this established relationship between a start-up's newly created knowledge stock and venture capital investments, which holds true in the short and long term. However, we further reveal that this effect is not uniformly because regional context factors matter. Regional context factors determine the signaling effect of a start-up's knowledge stock.

First, our results suggest that a region's geographical accessibility strengthens the signaling effect of a start-up's knowledge stock for venture capital investments. This geographical accessibility provides additional information for venture capitalists in their evaluation of the target object (Schwarz and Bless, 2007), i.e. a high-tech start-up. Our findings imply that the geographical accessibility provides contextual information about an potential investment to a venture capitalist, which induces assimilation effects (Schwarz and Bless, 2007). Hence, venture capitalist's positive evaluation of a start-up's knowledge stock becomes stronger when a region is more geographically accessible than in less geographically accessible regions. Such an assimilation effect occurs because geographical accessibility allows venture capitalists to conduct value-adding activities more effectively and efficiently, which increases start-up's success chances (Proksch et al., 2017). Venture capitalists anticipate these higher success chances based on the information about the regional context, and thus become more willing to invest. Our additional analyses further reveal that venture capitalists not only draw more positive evaluations about a start-up's newly created knowledge stock when a region is more densely populated but also when venture capitalists are already located nearby, and thus can reach start-ups more easily (Lutz et al., 2013).

Second, we find that a region's knowledge stock weakens the attractive power of a start-up's knowledge stock. This finding implies that, in line with context effects theory (Whetten, 2009), a region's knowledge stock sets a reference standard in the venture capitalist's mind, which helps the venture capitalist to evaluate a start-up by comparing it with this standard. In fact, our findings demonstrate that venture capitalists draw on contextual information, i.e. the region's newly created knowledge stock, when evaluating potential investees. This additional information from the regional context evokes contrast effects (Schwarz and Bless, 2007). When a start-up possesses a broad knowledge stock, this knowledge stock is more attractive in knowledge-sparse regions than in knowledge-intensive regions. In other words, start-ups can differentiate themselves from other start-ups in knowledge-sparse regions when they possess a broad knowledge stock. Therefore, such start-ups are successful in acquiring venture capital investments. Our robustness checks with alternative measures for the region's newly created knowledge stock reveal that venture capitalists draw on both regional innovation inputs (i.e., R&D expenditures and R&D personnel) as well as regional innovation outputs (i.e., patents) to compare potential investees with the regional standard.

3.5.2 Implications for Theory

This study contributes to research on the signaling value of a start-up's knowledge stock for venture capital investments. In this regard, existing research widely agrees that there is a signaling value of a start-up's knowledge stock in venture capital financing (e.g., Hsu and Ziedonis, 2013; Mann and Sager, 2007). In our longitudinal study, we confirm this effect for high-tech start-ups. Going beyond confirming this effect, we add knowledge in several ways.

We contribute to research by introducing context effects theory to the research setting of start-up financing. Existing research usually draws on signaling theory to derive context effects on the individual level (Colombo, 2021). However, this focus on signaling theory does neglect the role of context factors beyond the individual level, which seem to matter in venture capital financing as context effects theory suggests. Context effects theory originally stems from organizational research (Whetten, 2009) and is usually applied in consumer research (e.g., Laczniak and Teas, 2002; Meyers-Levy et al., 2010). Based on context effects theory (Whetten, 2009), we reveal that the regional context can evoke contrast and assimilation effects, which affect venture capitalists' investment decisions. In this regard, our results go beyond existing research and makes two specific contributions.

First, there are multiple studies analyzing context factors on the individual level influencing the effect of a start-up's knowledge stock on venture capital investments such as financing round and patent status (e.g., Haeussler et al., 2014; Hoenen et al., 2014). These studies usually draw on signaling theory to explain the effects of these individual context factors. However, based on context theory (Whetten, 2009), we argue and show that that the signaling effect of a start-up’s knowledge stock on venture capital investments not only depends on individual characteristics but also on factors on the regional level; that is, the regional context matters. In fact, we demonstrate that the signaling effect of a start-up’s knowledge stock is more effective in geographically accessible regions and less effective in knowledge-intensive regions.

Second, we add knowledge regarding the regional distribution of venture capital investments. Extant research reveals that venture capitalists usually spread their investments unequally across regions (e.g., Florida and Mellander, 2016; Lutz et al., 2013). However, these studies do not examine how these regional factors influence venture capitalists’ investment decisions. In this regard, we empirically demonstrate that regional factors such as geographical accessibility and knowledge stock correlate with venture capital investments (e.g., Florida and Mellander, 2016; Masiak et al., 2020). We further show that these regional factors can alter venture capitalists’ investment decisions, thus explaining the unequal distribution of investments across regions. Hence, we are able to further explain the venture capitalists’ regional bias towards certain regions, which is shown by several studies (e.g., Martin et al., 2002; Martin et al., 2005).

3.5.3 Implications for Practice

This study provides guidance for high-tech start-ups trying to obtain venture capital. Our findings suggest that high-tech start-ups should increase their knowledge stock to attract venture capitalists. For instance, start-ups should define their innovation strategy accordingly and reserve budgets for continuously conducting R&D to increase their newly created knowledge stock constantly. However, since R&D is expensive, this approach could be unfeasible for start-ups before receiving venture capital. Such money-constrained start-ups can follow alternative approaches to develop knowledge and apply for patents. Start-ups could cooperate with local universities or research institutes to benefit from their culture of knowledge generation (Belderbos et al., 2004). In such a win-win situation, start-ups benefit from co-created knowledge while universities can benefit from market data.

Moreover, we derive guidance for high-tech start-ups regarding where to locate their business. We find that regional factors can improve or impair their chances to acquire venture capital investments. Specifically, we advise start-ups that possess a broad knowledge stock to locate their business in geographically accessible regions because this allows a stronger involvement of venture capitalists who help commercialize this knowledge. In this regard, we advise venture capitalists to emphasize their value-adding activities and start-ups to take venture capitalists' advice because venture capitalists' activities usually increase a start-up's performance and success chances (e.g., De Clercq and Fried, 2005; Proksch et al., 2017). In this regard, both the venture capitalist and the investee should establish a good communication by, for example, having open discussions because a good communication is essential to build a successful partnership (De Clercq and Fried, 2005).

Nevertheless, start-ups also have to be careful when they choose where to locate their business because some regions can hamper start-ups' chances to obtain venture capital investments. Specifically, we advise high-tech start-ups not to move to very knowledge-intensive regions as venture capitalists evaluate a start-up's knowledge stock as less attractive in knowledge-intensive regions. To evaluate how knowledge-intensive a region is, start-ups should turn to national patent offices because they publish patent applications (Ernst, 2001), which are an indicator for the knowledge created in a region (Konon et al., 2018; Masiak et al., 2020).

Furthermore, our results provide guidance for policymakers aiming to build new entrepreneurial clusters in rather knowledge-sparse regions. Policymakers should attract innovative high-tech start-ups to such regions by emphasizing the increased chances to acquire financial resources from venture capitalists because these innovative start-ups become more attractive to venture capitalists because of arising contrast effects. Additionally, policymakers should concentrate on improving the region's geographical accessibility. On the one hand, policymakers should improve the regional infrastructure because this infrastructure can facilitate the interaction between venture capitalists and their investees (Bernstein et al., 2016). On the other hand, policymakers could provide subsidies to venture capitalists when these venture capitalists establish themselves in that region. This proximity helps high-tech start-ups' chances to acquire financial resources (Lutz et al., 2013). Alternatively, policymakers could provide governmental venture capital funds in the early phase of new entrepreneurial clusters. Such funds help to bridge the early equity gaps of start-ups and increase start-ups' chances to acquire follow-up funding from independent venture capitalists (Alperovych et al., 2020).

3.5.4 Limitations and Future Research

As we are the first to apply context effects theory to explain venture capital investments, we had to concentrate on specific context effects. Based on existing research (e.g., Florida and Mellander, 2016; Masiak et al., 2020), we derived that regional factors should be relevant in venture capital investments. Future research could build upon this study and context effects theory to derive and examine additional context factors. On the one hand, scholars could derive additional regional factors that may influence venture capitalist's investment decisions. On the other hand, research could concentrate on factors on other context levels, such as the country level. There could be country-specific factors that influence venture capitalists' investment decisions as, for example, formal institutions and cultural settings can explain varying activities by venture capitalists (Li and Zahra, 2012).

Additionally, we examine the number of venture capital investments as dependent variable to evaluate start-ups' fundraising success. While this is a very common approach in research on entrepreneurial finance (e.g., Conti et al., 2013a; Mann and Sager, 2007), other measures could be applied. For example, examining the raised amount of venture capital would be a more detailed measurement because the amounts of venture capital investments vary significantly from firm to firm (Hoenen et al., 2014), which could have implications for venture capitalists' involvement in their investees. Unfortunately, Spotfolio does provide information on the amount raised for less than ten percent of all financing rounds so that we could not conduct such an analysis. Nevertheless, we advise future research to replicate our approach and examine the amount raised as dependent variable.

4 Attracting Investors in Initial Coin Offerings: The Relevance of Specific Technological Capabilities for Fundraising Success (Study 3)

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Abstract

Drawing on signaling theory, we argue that signal vehicles for technological capabilities determine the fundraising success of ICOs. We analyze data from 357 ICOs between 2014 and 2020 using linear regressions. In addition to the effects of signal vehicles for technological capabilities, we account for campaign and venture characteristics. Our results reveal that ICO start-ups raise funds more successfully when they publish their source code. By following the logic of diffusion theory, we also find that ICO investors have characteristics similar to those of adopters of innovations. In this regard, we show that the effectiveness of signal vehicles for technological capabilities changes over time. Specifically, the early majority of adopters prefers a public source code, while the late majority prefers an own blockchain. Furthermore, patents do not serve as signal vehicle for technological capabilities. Consequently, we provide guidance for start-ups on how to conduct successful ICO fundraising.

Keywords

Initial coin offerings, Entrepreneurial finance, Technological capabilities, Signaling theory

Publication

Stephan Philippi, Monika C. Schuhmacher and Nicolai Bastian (2021), "Attracting Investors in Initial Coin Offerings: The Relevance of Specific Technological Capabilities for Fundraising Success", Review of Corporate Finance: Vol. 1: No. 3-4, pp 455-485.

http://dx.doi.org/10.1561/114.00000010

4.1 Introduction

In the last years, far-reaching changes and developments have influenced the field of entrepreneurial finance, giving rise to new ways of fundraising. One new form of fundraising that has attracted the attention of both practitioners and researchers is ICOs. An ICO refers to an open call for funding, in which start-ups raise money from a crowd of investors, who receive digital tokens in exchange for their investment (Adhami et al., 2018). Tokens are units of value and often sold in the form of cryptocurrencies (Fisch, 2019). As such, they refer to a digital medium of exchange that draws on a distributed ledger technology, such as the blockchain technology (Chen et al., 2021). This technology allows efficient, verifiable, and permanent transactions between two parties (Iansiti and Lakhani, 2017), thus providing the basis for fundraising through ICOs.

In recent times, ICOs have recorded the most notable development among new forms of entrepreneurial finance (Bellavitis et al., 2021). Since the first ICO in 2013, start-ups have raised more than 31 billion USD through this new fundraising method (Davies et al., 2020). However, the ICO market is widely unregulated, which leads to considerable uncertainties and information asymmetries between start-ups and investors (Adhami et al., 2018). In this environment, reducing information asymmetries from the perspective of investors is of utmost importance for start-ups to receive the needed investment. According to signaling theory (Connelly et al., 2011; Spence, 1973), start-ups can reduce information asymmetries and convince investors of their investment worthiness by sending observable signal vehicles. Potential investors observe and interpret these signal vehicles, which allows them to draw conclusions about an unobservable signal of the start-up’s quality (Schuhmacher et al., 2018), which ultimately increases fundraising success.

Extant research shows the effectiveness of different signal vehicles for different forms of entrepreneurial finance, such as IPOs, venture capital, and equity crowdfunding. These signal vehicles can be grouped into, for example, the categories campaign characteristics (e.g., Vismara, 2016), venture characteristics (e.g., Eddleston et al., 2016), or technological characteristics (e.g., Ahlers et al., 2015). However, knowledge from entrepreneurial finance research is neither fully applicable nor sufficient alone to explain ICOs, because ICOs differ from other forms of entrepreneurial finance in several ways (Chen, 2019).

First, ICOs differ from IPOs. While IPO firms are usually large firms, ICOs are mostly conducted by small start-ups (Howell et al., 2020). At the same time, the IPO market is more regulated than the ICO market (Ante et al., 2018). Thus, signal vehicles should be more important to reduce information asymmetries and attract investors in the ICO context than in the IPO context. Second, basically anyone can invest in an ICO, so ICO investors are often private investors (Huang et al., 2019). These rather unsophisticated investors differ in their investment decisions from professional investors, such as venture capitalists, in that they tend to take less time to evaluate an investment project and invest smaller amounts of money (Fisch et al., 2021). Therefore, as in equity crowdfunding campaigns (Ahlers et al., 2015), start-ups running an ICO might need to use very clear and easily observable signal vehicles (Chen, 2019). Third, although ICOs resemble the process of equity crowdfunding (Perez et al., 2020), they differ from equity crowdfunding as well. ICO start-ups are usually technology-driven, knowledge-intensive, and innovative (Adhami et al., 2018; Fisch, 2019), so ICO investors should be more knowledgeable and tech-savvy than investors in equity crowdfunding, turning them into subject matter experts who want to know about the start-up's technological background. Thus, compared with effective signal vehicles in equity crowdfunding, such as venture characteristics (Ahlers et al., 2015), we assume that signal vehicles, which signal a start-up's technological capabilities, play an especially important role in the ICO context (Fisch, 2019). Given these differences, we argue that research needs to zoom in on signaling in the ICO context and specifically on signaling technological capabilities.

Studies on success factors of ICOs in general and on signaling technological capabilities in particular are scarce (see Table 4.1 for an overview). Research in the ICO context mainly concentrates on campaign characteristics, such as equity retention and funding volume (e.g., Giudici et al., 2020; Roosenboom et al., 2020), and venture characteristics, such as team size or social contacts in terms of advisors (e.g., Chen, 2019; Giudici and Adhami, 2019). Furthermore, some studies examine the effects of specific technological characteristics. Most of these articles focus on the publication of the source code as a driver of fundraising success (e.g., Adhami et al., 2018; Howell et al., 2020). Considering the technological environment of ICOs and the tech-savviness of ICO investors (Fisch, 2019), research on other potential signal vehicles to signal technological capabilities is lacking. Consequently and in line with signaling theory (Spence, 1973), we argue that, apart from the publication of the source code, developing a new blockchain and having a patent are effective signal vehicles for start-ups to signal their technological capabilities, which is looked for by ICO investors (Fisch, 2019).

Table 4.1: Literature Overview (Study 3)

Article	Signal Vehicles for Technological Capabilities			Study Accounts for		Sample
	Public Source Code	**Own Block-chain**	**Patent**	**Campaign Characteristics**	**Venture Characteristics**	
Adhami et al. (2018)	**Yes**	No	No	**Yes**	No	253 ICOs (2014-2017)
Ante et al. (2018)	No	No	No	**Yes**	No	278 ICOs (2013-2017)
An et al. (2019)	No	No	No	**Yes**	**Yes**	715 ICOs (2014-2018)
Chen (2019)	**Yes**	No	No	**Yes**	**Yes**	626 ICOs (2015-2018)
Fisch (2019)	**Yes**	No	**Yes**	**Yes**	**Yes**	456 ICOs (2016-2018)
Giudici and Adhami (2019)	**Yes**	No	No	**Yes**	**Yes**	935 ICOs (2014-2017)
Howell et al. (2020)	**Yes**	No	No	**Yes**	**Yes**	1,520 ICOs (2013-2019)
Domingo et al. (2020)	No	No	No	**Yes**	**Yes**	125 ICOs (2017-2018)
Giudici et al. (2020)	**Yes**	No	No	**Yes**	**Yes**	931 ICOs (2015-2018)
Momtaz (2020a)	No	No	No	**Yes**	**Yes**	495 ICOs (2015-2018)
Momtaz (2020b)	No	No	No	No	**Yes**	213 ICOs (2015-2018)
Perez et al. (2020)	No	No	No	No	No	537 ICOs (2018)
Roosenboom et al. (2020)	**Yes**	No	No	**Yes**	**Yes**	630 ICOs (2015-2017)
This Study	***Yes***	***Yes***	***Yes***	***Yes***	***Yes***	***357 ICOs (2014-2020)***

The aim of this study is to close this research gap by investigating different signal vehicles for technological capabilities and their impact on ICO fundraising success. Specifically, we address the following research question: *Which signal vehicles for technological capabilities positively affect ICO fundraising success?* To answer this question, we collected data on 357 ICOs that took place between 2014 and 2020. We analyzed these ICOs by conducting linear regressions while also running separate analyses for 2017, 2018, and 2019, which enabled us to examine the development of these signal vehicles' effectiveness over time. In this process, we also accounted for campaign and venture characteristics, which are additional drivers of ICO fundraising success (e.g., Roosenboom et al., 2020).

This study contributes to ICO research in multiple ways. First, research on ICOs usually concentrates on one or two categories of ICO fundraising drivers and examines samples of ICOs up to 2018 or 2019 (see Table 4.1). We go beyond these studies by creating a more comprehensive and realistic picture, as we account for all three major categories of ICO fundraising drivers—technological, venture, and campaign characteristics—and analyze a sample of ICOs from 2014 to 2020.

Second, we add to ICO research on the signaling effect of technological capabilities. So far, research has mainly concentrated on one signal vehicle: the underlying source code. Extant studies provide ambiguous results with regard to the effectiveness of publishing the source code in signaling technological capabilities (e.g., Adhami et al., 2018; Fisch, 2019). While research usually concentrates on GitHub as a means to publish the source code (e.g., Fisch, 2019; Howell et al., 2020), we widen the search scope by including white papers and websites as well. Thus, we are able to better mirror reality regarding the means of publishing the source code. With this more realistic operationalization, we demonstrate the effectiveness of publishing the source code in attracting ICO investors.

Third, given the technological nature of ICOs, we argue that research needs to delve deeper into technological capabilities and investigate several corresponding signal vehicles simultaneously. Hence, besides publishing a source code, we investigate the relevance of two additional signal vehicles for technological capabilities: developing an own blockchain and having a patent. The few studies that investigate the underlying blockchain focus on the use of the Ethereum blockchain and how this specific blockchain affects ICO fundraising success (e.g., Giudici et al., 2020). As such, prior research neglects one common practice of ICO start-ups: developing an own blockchain. To close this gap, we examine differences between start-ups that build their own blockchain and start-ups that adapt an existing blockchain, such as Ethereum. In this way, we account for two essentially different approaches of ICO start-ups. Indeed, we show that developing an own blockchain is as beneficial for ICO start-ups as adapting an existing one.

Finally, we contribute to ICO research by applying the logic of diffusion theory (Rogers, 2003) to better understand the role of specific signal vehicles in ICO fundraising success. Although existing studies investigate ICOs across several periods (see Table 4.1), to our knowledge, no study investigates whether the effectiveness of these signal vehicles changes over time. We find that the three investigated signal vehicles for technological capabilities vary in their effectiveness across years. This finding is of utmost importance not only in the ICO context but also for entrepreneurial finance in general, because we demonstrate that the effectiveness of signals and signal vehicles is not constant.

4.2 Theory and Hypotheses

4.2.1 Signaling Theory

Signaling theory explains how two actors—signal sender and signal receiver—can behave in situations of high uncertainty and asymmetric information (Spence, 1973). Signal senders are insiders who are better informed than signal receivers (Spence, 1973). Thus, insiders can send signals to communicate information to less informed outsiders (Connelly et al., 2011). To be effective, these signals need to fulfill two conditions: they need to be observable to outsiders and costly to realize for insiders (Spence, 1973). In this context, costs are not only monetary but also nonmonetary, such as time, effort, and reputation (Fisch, 2019). Signal receivers can interpret these signals to draw conclusions about the expected quality of the signal sender (Spence, 1973). As a result, signal receivers gain information so that information asymmetries decrease (Spence, 1973). Schuhmacher et al.'s (2018) specification of signaling theory sheds more light on how signals transmit information. They differentiate signal vehicles and signals as two distinctive constructs. A signal vehicle is an observable medium that transmits information, and it becomes a signal only when the signal receiver interprets it and draws a conclusion about the meaning of this signal vehicle (Schuhmacher et al., 2018).

Studies in entrepreneurial finance often apply signaling theory (e.g., Baum and Silverman, 2004). In this context, start-ups possess more information about their quality than investors do (Myers and Majluf, 1984). Therefore, start-ups can use signal vehicles to signal their quality, reduce information asymmetries, and convince investors of their investment worthiness (Audretsch et al., 2012). Signaling theory is also applicable in the ICO context, as information asymmetries characterize relationships between ICO start-ups and ICO investors (Momtaz, 2020a). Ante et al. (2018) examine, for example, how team size affects ICO fundraising success. In this situation, team size functions as an observable signal vehicle, which ICO investors can interpret as signal the availability of human capital. Investors make this interpretation because the aggregated human capital is greater when several employees bring in and combine their individual skills and expertise (Iyigun and Owen, 1998), which usually leads to greater firm performance (Crook et al., 2011).

4.2.2 Hypotheses Development

Drawing on signaling theory (Spence, 1973), we propose that different signal vehicles that signal a start-up's technological capabilities play an important role in the ICO context. Specifically, we expect that publishing the source code, developing a new blockchain, and having a patent are relevant signal vehicles. According to entrepreneurial finance research, start-ups' technological capabilities are an effective signal to attract investors (e.g., Mann and Sager, 2007), because these capabilities result in greater firm performance (Ortega, 2010). Considering this performance-increasing effect, we expect that ICO investors perceive ICO start-ups that signal their technological capabilities as more promising, such that their willingness to invest increases. Thus, ICO start-ups that can signal their technological capabilities should have more ICO fundraising success.

4.2.2.1 Public Source Code as Signal Vehicle for Technological Capabilities

Start-ups that conduct an ICO are blockchain-based companies (Ante et al., 2018). Development of these start-ups usually occurs in the form of programming activities, which result in a source code (Fisch, 2019). This source code provides the basis for start-ups because it embodies the digital tokens they sell to investors during an ICO (Cohney et al., 2019). For example, within the source code, start-ups set the functionality of the digital tokens, which they sell through an ICO (Cohney et al., 2019). In other words, each ICO start-up has an underlying source code and must ensure the technical suitability of that source code for the particular founding project. We argue that ensuring this technical suitability can be an observable signal vehicle for technological capabilities.

ICO start-ups can decide whether to publish their source code or not, which mainly happens in a white paper, on a website, or in an online repository (Adhami et al., 2018). By publishing the source code, ICO start-ups create transparency (Howell et al., 2020) because the source code provides insights into the technical suitability and current state of the project (Adhami et al., 2018). Only start-ups that are confident about their technological capabilities would risk publishing the source code and potentially reveal a lack of technological capabilities to the public (Roosenboom et al., 2020).

In line with signaling theory, publishing the source code fulfills both conditions of an effective signal vehicle. First, publishing the source code is observable because the source code is publicly available in a white paper, on a website, or in an online repository (e.g., GitHub), so that the community can observe it (Adhami et al., 2018; Howell et al., 2020). Second, publishing the source code is costly for ICO start-ups because they must put in time and effort to create a source code, which does not raise quality concerns within the tech-savvy community. Publishing the source code is also costly for start-ups because the risks of hacks and cyber theft are higher when the source code is publicly available (Adhami et al., 2018). Therefore, we hypothesize:

Hypothesis 1: If the start-up publishes the source code, ICO fundraising is more successful than if the start-up does not publish the source code.

4.2.2.2 Own Blockchain as Signal Vehicle for Technological Capabilities

In the early stages of development, ICO start-ups need to decide on the underlying blockchain of the founding project. In general, start-ups can build their business on an existing blockchain, such as Ethereum, or develop their own blockchain (Momtaz, 2020a). We argue that developing an own blockchain is a signal vehicle that can convey the ICO start-up's technological capabilities because blockchain technology "is a revolutionary and disruptive technological innovation" (Fisch, 2019, p. 1). Possessing technological capabilities is essential for firms to develop any new technology or innovation (Kyläheiko et al., 2011), such as developing an own blockchain. However, as technological capabilities are not observable, developing an own blockchain can be an observable way to signal a start-up's technological capabilities to ICO investors.

Following the logic of signaling theory, developing an own blockchain fulfills both conditions to be an effective signal vehicle. First, the decision to develop an own blockchain for the founding project is observable because ICO start-ups present their decision for the underlying blockchain in their white papers (Adhami et al., 2018). Second, developing an own blockchain is costly because start-ups need to conduct extensive programming activities to do so. Although adapting an existing blockchain also requires programming activities, developing an own blockchain requires more effort and technological capabilities. These activities come with higher expenditures in terms of time and/or money. On the one hand, developing a blockchain usually takes several months until it is ready for launch (Agrawal, 2020). On the other hand, developing a blockchain is expensive because start-ups need to have capable blockchain developers, whose salaries are higher than those of typical software developers (Hired, 2019). Thus, we hypothesize:

Hypothesis 2: If the start-up develops its own blockchain, ICO fundraising is more successful than if the start-up builds on an existing blockchain.

4.2.2.3 Patent as Signal Vehicle for Technological Capabilities

Per its definition by the United States Patent and Trademark Office (USPTO), a technology must be novel, useful, nonobvious, and adequately described to be patented (USPTO, 2020). This definition implies that obtaining a patent requires technological capabilities. Hence, we argue that having a patent can serve as a signal vehicle to signal technological capabilities. On the one hand, when start-ups develop a patent, they must own a novel technology, whose development requires extensive technological capabilities (Kyläheiko et al., 2011). On the other hand, start-ups need to possess technological capabilities to adequately describe their new technology, because the patent office is unlikely to grant a patent if the start-up is unable to describe the new technology adequately (USPTO, 2020). Considering this close connection between patents and technological capabilities, various studies in the research fields of entrepreneurship and innovation assess patents to draw conclusions about a firm’s technological capabilities (e.g., Kotha et al., 2011; Lee et al., 2009).

In line with signaling theory, a patent also fulfills both conditions of an effective signal vehicle. First, patents are observable because they refer to legal rights that are registered through a patent office and published during the registration process (Gick, 2008). Second, a patent is costly because applying for and holding a patent is a money- and time-consuming process (Thomä and Bizer, 2013). For example, obtaining a patent in the United States costs 38,000 USD on average (Graham et al., 2009). Thus, we hypothesize:

> *Hypothesis 3: If the start-up has at least one patent, ICO fundraising is more successful than if the start-up does not have any patents.*

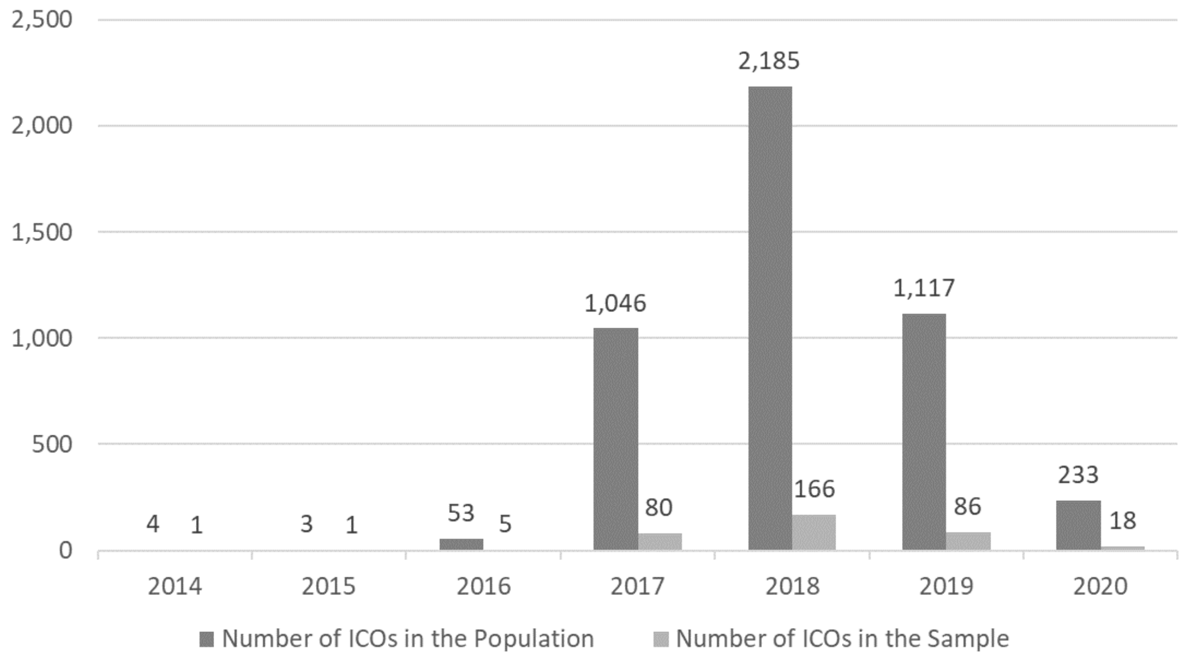
4.3 Methodology

4.3.1 Sourcing of Sample

To acquire the sample for our study, we conducted multiple steps. First, we collected all names and finishing dates of ICOs from January 2014 until October 2020. Programming a web scraper in Visual Basics for Applications allowed us to collect data from seven ICO databases: ICOdata, ICOdrops, ICOBench, ICORating, ICOcheck, Iconiq Lab, and ICOHolder. We merged the data from all sources and removed duplicates of ICOs. In case of missing information, we turned to other sources and collected the finishing date from the white paper, website, or news posts of the corresponding start-up. This process resulted in a basic population of 4,641 ICOs. More specifically, the list consists of four ICOs in 2014, three ICOs in 2015, 53 ICOs in 2016, 1,046 ICOs in 2017, 2,185 ICOs in 2018, 1,117 ICOs in 2019, and 233 ICOs in 2020. Figure 4.1 depicts the distribution of ICOs per year in the basic population.

Second, as we had to collect all necessary information for the operationalization of our variables from white papers, websites, and databases, we drew a random sample from this population to make data acquisition manageable (Bradonjic et al., 2019). The application of sample size calculators suggested analyzing at least 355 ICOs from our population of 4,641 ICOs to reach a reasonable confidence level of .90 and a margin of error of .05 (Cumming and Finch, 2005). While drawing the random sample from this population, we weighted cases by year so that our sample reflects the actual share of ICOs per year. Thus, we increased the size of our sample slightly, leading to a final sample of 357 ICOs: one ICO from 2014, one ICO from 2015, five ICOs from 2016, 80 ICOs from 2017, 166 ICOs from 2018, 86 ICOs from 2019, and 18 ICOs from 2020 (see Figure 4.1).

Figure 4.1: Distribution of Initial Coin Offerings per Year (Study 3)



Third, we collected data for the variables of interest for each of the 357 ICOs. To start, we gathered information from the white papers and websites of the start-ups. If a start-up had no such data available, we obtained the information from the selected databases. We cross-checked the information obtained from the databases for each variable to account for inconsistencies in reporting and accepted deviations below ten percent. In case of such small deviations, we used the database with the highest accuracy, in line with Benedetti and Kostovetsky (2021). We followed their suggestion and prioritized the databases as follows: (1) ICOdata, (2) ICOdrops, (3) ICObench, (4) ICOrating, (5) ICOcheck, (6) Iconiq Lab, and (7) ICOHolder. If no data were available for a variable or the deviation between databases exceeded ten percent, we substituted the case with another randomly selected case from our ICO list.

4.3.2 Variables

4.3.2.1 Dependent Variable

We measured ICO fundraising success by examining the variable *amount raised*, which reflects the total amount of money raised from investors during an ICO. Thus, we followed a wide array of studies to measure ICO fundraising success (e.g., Ante et al., 2018; Fisch, 2019). We conducted a log transformation because of the skewness of this variable.

4.3.2.2 Independent Variables

We examined three variables that function as signal vehicles for technological capabilities. First, the variable *public source code* indicates whether the source code was (partly) published. Start-ups usually publish their source code in white papers, on their websites, or in online repositories. If none of these sources provided any insights, we coded the variable as no public source code. Hence, we followed the typical approach in ICO research to examine the publication of source code (e.g., Giudici and Adhami, 2019).

Table 4.2: Description of Variables (Study 3)

Variable	Description	Adapted from
Dependent Variable: Fundraising success		
Amount raised (log)	Total amount of funds raised in an ICO (in percent). Due to skewness, this variable was logarithmized.	Ante et al. (2018)
Independent Variables: Technological Characteristics		
Public Source Code	Dummy variable that equals 1 if the ICO start-up published at least parts of the source code of its technology and 0 otherwise	Adhami et al. (2018)
Own Blockchain	Dummy variable that equals 1 if the ICO start-up developed an own blockchain and 0 otherwise.	-
Patent	Dummy variable that equals 1 if the ICO start-up had at least one patent (application or grant) and 0 otherwise.	Fisch (2019)

Table 4.2: Description of Variables (Study 3) (cont.)

Variable	**Description**	**Adapted from**
Control Variables: Campaign Characteristics		
Duration	The number of days between start and end of an ICO.	Fisch (2019); Giudici and Adhami (2019)
Hardcap (log)	The hardcap (major financial goal) as defined by the start-up at the beginning of an ICO (in USD). If the start-up declared the hardcap in a cryptocurrency, we computed the equivalent prices in USD based on the market price of the respective cryptocurrency on the corresponding date. Due to skewness, this variable was logarithmized.	Giudici et al. (2020)
ICO Price (log)	Price of the issued tokens at the end of the ICO (in USD). If the start-up declared the ICO price in a cryptocurrency, we computed the equivalent prices in USD based on the market price of the respective cryptocurrency on the corresponding date. Due to skewness, this variable was logarithmized.	Roosenboom et al. (2020)
Presale Program	Dummy variable that equals 1 if the ICO had a presale program and 0 otherwise.	Fisch (2019); Giudici and Adhami (2019)
Bounty Program	Dummy variable that equals 1 if the ICO had a bounty program and 0 otherwise.	Adhami et al. (2018)
Airdrop Program	Dummy variable that equals 1 if the ICO had an airdrop program and 0 otherwise.	Howell et al. (2020)
Referral Program	Dummy variable that equals 1 if the ICO had a referral program and 0 otherwise.	-
Retained Tokens	The share of tokens distributed to team members and advisors as defined by the start-up for allocation after the ICO (in percent).	Vismara (2016)
Cryptocurrencies Only	A dummy variable that equals 1 if the ICO accepted only cryptocurrencies for investments during fundraising and 0 if they also or solely accepted legal tenders.	Roosenboom et al. (2020)
Year Dummies	Seven dummy variables (2014 to 2020) reflecting the year, in which the ICO ended.	Fisch (2019)
Token Dummies	Six dummy variables reflecting the type of a token: Utility token, security token, currency token, asset token, voting token, and other token.	Giudici et al. (2020)
Control Variables: Venture Characteristics		
Established Start-up	Dummy variable that equals 1 if the start-up was already an established business prior to the ICO and 0 otherwise.	-
Team Size	The number of team members who are employed by the start-up.	Roosenboom et al. (2020)
Advisor Size	The number of advisors who supported the start-up.	An et al. (2019); Ante et al. (2018)
Social Media Channels	The sum of social media channels utilized by the start-up. In this regard, we consider Reddit, Bitcointalk, Twitter, Facebook, Telegram, Medium, and Slack.	Ante et al. (2018); Howell et al. (2020)
Country Dummies	55 dummy variables reflecting the country, in which the ICO start-up was headquartered.	Howell et al. (2020); Momtaz (2020b)

Second, the variable *own blockchain* reflects whether ICO start-ups developed their own blockchain or adapted an already-existing blockchain. Start-ups usually explain their choice of the underlying blockchain in their white papers or on their websites (Adhami et al., 2018). Thus, we reviewed their explanations in these sources to collect the name of the underlying blockchain for each ICO. Then, we created a binary variable reflecting whether the start-up developed its own blockchain or adapted an already-existing blockchain.

Third, the variable *patent* specifies whether the start-up indicated having at least one patent before the ICO. We scanned all white papers and websites to determine whether a start-up mentioned a pending patent application or a granted patent. We considered both patent applications and grants because both types of patents exert positive effects on technological capabilities and fundraising success (Baum and Silverman, 2004). Through our scanning process, we created a dummy variable reflecting whether the start-up had at least one patent (application or grant) or not. With this approach of a binary variable, we followed many studies in entrepreneurial finance and ICO research (e.g., Fisch, 2019; Mann and Sager, 2007).

4.3.2.3 Control Variables

Because many studies show that campaign and venture characteristics also determine ICO fundraising success, we included several control variables. In terms of campaign characteristics, we accounted for *duration* of an ICO, because research shows that shorter ICOs are more successful (e.g., Fisch, 2019). In addition, we controlled for two financial aspects of the campaign: *hardcap* and *ICO price*. The hardcap constitutes the major financing goal of an ICO (Giudici and Adhami, 2019). Therefore, we controlled for the size of the fundraising project. The ICO price reflects the price of the issued tokens so that we are able to control for the value of the campaign's underlying token. We log-transformed both variables because of their skewness. Furthermore, to control for the existence of various programs to attract investors before or during an ICO, we created four dummy variables: *presale program*, *bounty program*, *airdrop program*, and *referral program* (e.g., Adhami et al., 2018; Howell et al., 2020). Moreover, equity retention can signal greater trust of the founders in the own project (Vismara, 2016), so we included the variable *retained tokens*, which captures the share of tokens distributed to the team and advisors (Roosenboom et al., 2020). We also accounted for how investors can participate in an ICO with the dummy variable *cryptocurrencies only* (Roosenboom et al., 2020). Finally, we accounted for year and token effects with seven dummy variables for the years 2014–2020 and six dummies for the nature of the underlying token: *utility*, *security*, *currency*, *asset*, *voting*, or *other token* (Giudici and Adhami, 2019).

In terms of venture characteristics, we controlled for the record of accomplishment of a start-up by examining the variable *established start-up*. This variable accounts for whether the start-up was already an established start-up before the ICO or began operating right before the ICO. Furthermore, we controlled for venture characteristics in terms of human and social capital. Here, we controlled for *team size* (e.g., Chen, 2019), *advisor size* (e.g., Ante et al., 2018), and *social media channels* (e.g., Howell et al., 2020). Finally, we created 55 country dummies to account for country effects, which can affect ICO fundraising (e.g., Momtaz, 2020a). Table 4.2 provides an overview of all study variables.

4.3.3 Methodology

To test the effects of the independent variables on ICO fundraising success, we conducted ordinary least square regressions with the log-transformed dependent variable *amount raised*. The regression equation for the full model is

$$log(amount\ raised + 1) = B_0 + B_1\ public\ source\ code_i + B_2\ own\ blockchain_i$$
$$+ B_3\ patent_i + x_i + \varepsilon,$$

where B_0 is the intercept, $B_{1\text{-}3}$ are the unstandardized regression coefficients, x_i is the vector of control variables, and ε is the error term.

4.4 Results

4.4.1 Correlations

Initially, we calculated bivariate correlations, which we present in Table 4.3. Although there are some significant bivariate correlations, there are no problematic correlations. We find the highest correlations between the variables amount raised and social media channels ($r = .369$) and between public source code and social media channels ($r = .327$). Table 4.3 also lists VIFs of the full model. We find an average VIF of 1.626 and observe that all individual VIFs are well below the threshold of 5, which is a typical threshold to assess multicollinearity problems (Hair, Ringle, and Sarstedt 2011). Overall, descriptive statistics indicate that there are no problems of (multi)collinearity affecting our results.

Table 4.3: Correlations (Study 3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	VIF
Dependent Variable: Fundraising success																		
(1) *Amount Raised (log)*	1.000																	
Independent Variables: Signal Vehicles for Technological Capabilities																		
(2) *Public Source Code*	.291	1.000																1.55
(3) *Own Blockchain*	.146	.112 *	1.000															1.51
(4) *Patent*	.033	–.040	.010	1.000														1.50
Control Variables: Campaign Characteristics																		
(5) *Duration*	–.146	–.229 ***	–.159 **	–.017	1.000													2.09
(6) *Hardcap (log)*	.244	–.090	.056	–.011	.152 **	1.000												1.53
(7) *ICO Price (log)*	.014	–.088	–.084	–.069	.059	.157 **	1.000											1.33
(8) *Presale Program*	–.048	.081	.091	–.098	.023	.121 *	–.095	1.000										1.50
(9) *Bounty Program*	.076	.115 *	–.033	–.061	.064	–.046	.009	.141 **	1.000									1.57
(10) *Airdrop Program*	.097	.051	–.005	.047	.049	–.003	–.118 *	.122 *	.203 ***	1.000								1.70
(11) *Referral Program*	.072	.061	–.053	–.029	.103	.069	–.043	.199 ***	.302 ***	.284 ***	1.000							1.65
(12) *Token Retention*	.156	.144 **	.141 **	.088	–.087	–.014	–.069	.000	–.048	.080	–.026	1.000						1.42
(13) *Cryptocurrencies Only*	.159	.056	.019	–.149 **	–.176 **	–.157 **	–.085	.022	.078	.007	–.087	.097	1.000					1.60
Control Variables: Venture Characteristics																		
(14) *Established Start-up*	–.061	–.042	–.126 **	.106 *	.251 ***	.055	.043	–.033	–.004	.019	.014	–.039	–.187 ***	1.000				1.76
(15) *Team Size*	.219	.159 **	.073	.087	–.077	.061	–.082	.116 *	.001	.134 *	.049	.098	–.067	.038	1.000			1.47
(16) *Advisor Size*	.252	.188 ***	.203 ***	.128 *	–.089	.065	–.140 **	.146 **	–.028	.084	.073	.099	.067	.063	.242 ***	1.000		1.62
(17) *Social Media Channels*	.369	.327 ***	.070	–.025	–.219 ***	.030 *	–.073	.166 **	.229 ***	.110 *	.235 ***	.121 *	.104 *	–.052	.148 **	.286 ***	1.000	2.21

Notes: *** Correlation is significant at the .001 level. ** Correlation is significant at the .010 level. * Correlation is significant at the .050 level. VIFs refer to Model 2.

4.4.2 Main Analyses

Table 4.4 displays the results of our regression analysis. Model 1 includes only the control variables, regarding both campaign and venture characteristics. Model 2 constitutes the full model, consisting of all the control variables as well as independent variables regarding the three signal vehicles for technological capabilities.

Table 4.4: Regression Results (Study 3)

	Model 1				**Model 2**			
Dependent variable:	**Amount Raised (log)**							
	B	**(S.E.)**	**p-value**		**B**	**(S.E.)**	**p-value**	
(Constant)	–7.195	(1.608)	.498		–8.061	(1.392)	.439	
Control Variables: Campaign Characteristics								
Duration	–.002	(.003)	.436		–.000	(.003)	.991	
Hardcap (log)	.658	(.153)	.000	***	.721	(.152)	.000	***
ICO Price (log)	.212	(.210)	.314		.239	(.206)	.247	
Presale Program	–.824	(.461)	.075		–.807	(.459)	.080	
Bounty Program	.067	(.472)	.887		.020	(.461)	.966	
Airdrop Program	.284	(.390)	.467		.301	(.381)	.431	
Referral Program	–.083	(.380)	.827		–.123	(.372)	.741	
Token Retention	–.461	(2.008)	.818		–1.566	(1.995)	.433	
Cryptocurrencies Only	1.327	(.433)	.002	**	1.460	(.437)	.001	**
Control Variables: Venture Characteristics								
Established Start-up	–.250	(.454)	.582		–.153	(.445)	.731	
Team Size	.803	(.170)	.000	***	.717	(.168)	.000	***
Advisor Size	.081	(.027)	.003	**	.075	(.026)	.004	**
Social Media Channels	.088	(.041)	.033	*	.061	(.042)	.147	
Independent Variables: Signal Vehicles for Technological Capabilities								
Public Source Code					1.585	(.409)	.000	***
Own Blockchain					.677	(.640)	.291	
Patent					.194	(.753)	.797	
Country Dummies	Included				Included			
Year Dummies	Included				Included			
Token Dummies	Included				Included			
No. of observations	357 ICOs				357 ICOs			
F-value	3.510 (p-value = .000)				3.750 (p-value = .000)			
R^2	.500				.529			
Adjusted R^2	.358				.388			

Notes: *** p<.001. ** p<.01. * p<.050; standard errors in parentheses.
Results for country, year, and token dummies are not displayed for reasons of clarity.

First, we turn to Model 1 to examine the effects of our control variables. In terms of campaign characteristics, we find that hardcap (B = .658, p = .000) and cryptocurrencies only (B = 1.327, p = .002) increase ICO fundraising success. The remaining campaign characteristics do not exert significant impacts on fundraising success, which is in line with prior research (e.g., Howell et al., 2020; Roosenboom et al., 2020). In terms of venture characteristics, we find that the variable established start-up does not affect ICO fundraising success (B = –.250, p = .582), while team size (B = .803, p = .000), advisor size (B = .081, p = .003), and social media channels (B = .088, p = .033) significantly increase ICO fundraising success. These findings also support multiple studies in this research field (e.g., An et al., 2019; Ante et al., 2018).

Second, we turn to Model 2 in Table 4.4 to test our hypotheses. We observe that public source code has a positive and significant coefficient (B = 1.585, p = .000). Thus, in line with Hypothesis 1, we show that publishing the source code increases ICO fundraising success. Next, the variable own blockchain does not have a significant effect on ICO fundraising success (B = .677, p = .291). In other words, we find that developing an own blockchain instead of using an existing blockchain does not lead to higher ICO fundraising success. Therefore, we find no support for Hypothesis 2. Finally, our regression results reveal that the variable patent is not a significant predictor of ICO fundraising success (B = .194, p = .797). This indicates that start-ups with a patent are not able to acquire more financial resources through an ICO than start-ups without patents. As a result, we find no support for Hypothesis 3.

4.4.3 Additional Analyses

We were somewhat surprised by the finding that two of the three proposed signal vehicles for technological capabilities turn out to have no significant effect on ICO fundraising success. Accordingly, we turned to analyzing signal vehicles' effectiveness over time by conducting separate analyses for the years 2017, 2018, and 2019.[1]

We decided to run these separate analyses over time because dramatic changes characterize the ICO market (Bellavitis et al., 2021). We expect that these changes also affect ICO investors' behavior over time. ICOs were a technological innovation when first used in 2013. Their adoption rate should follow the logic of the diffusion curve (Rogers, 2003). Figure 4.1 shows that ICOs indeed exhibit this typical bell curve. The number of ICOs slowly increased from 2014 to 2016; i.e., innovators were active in this phase. In 2017, ICOs gained market traction, with early adopters coming into the market. The number of ICOs peaked in 2018, with the early

[1] We cannot conduct these additional analyses for the years 2014, 2015, 2016, and 2020 because of the small subsample sizes.

majority in place at this time. In 2019 and 2020, the diffusion of ICOs slowed down, with the late majority and even first laggards coming into the market.

We assume that ICO investors exhibit typical characteristics along this diffusion curve. For example, innovators, early adopters, and the early majority are usually more innovative and have technological know-how in the domain of the respective innovation (Dedehayir et al., 2017), while the late majority and laggards are less innovative and tech-savvy. Therefore, we propose that the effectiveness of signal vehicles for technological capabilities should change over time. Publishing the source code should be more relevant in the early years because ICO investors were more tech-savvy, so they were able to read the source code. In later phases, the source code should become less relevant, while more easily observable signal vehicles for technological capabilities, such as developing an own blockchain and having a patent, become more relevant.

Table 4.5 shows the regression results for all ICOs in 2017 (N = 80). Here, we find that the signal vehicles *public source code* (B = .145, p = .750), *own blockchain* (B = 1.737, p = .304), and *patent* (B = –.780, p = .402) do not have significant effects on ICO fundraising success. However, the analysis of the 166 ICOs from 2018 shows that the public source code becomes a significant driver of ICO fundraising success (B = 2.797, p = .001) while *own blockchain* (B = .520, p = .565) and *patent* (B = 1.091, p = .501) do not significantly influence ICO fundraising success (see Table 4.6). Finally, analyzing the 2019 subsample of 86 ICOs, we find that *public source code* (B = 1.245, p = .083) and *patent* (B = .432, p = .686) have no significant effects on ICO fundraising while developing an *own blockchain* significantly increases ICO fundraising success (B = 8.502, p = .011, see Table 4.7).

In summary, we find partial support for our proposition, as our results show that the effectiveness of signal vehicles for technological capabilities indeed changes over time. Surprisingly, signal vehicles were rather irrelevant when early adopters entered the market in 2017. At the time the early majority came into the market in 2018, publishing the source code became an effective signal vehicle for technological capabilities. For the late majority, which entered the market in 2019, developing an own blockchain became more relevant to signal technological capabilities to ICO investors. Having a patent remains the only ineffective signal vehicle for signaling technological capabilities to ICO investors over time.

Table 4.5: Regression Results 2017 (Study 3)

	Model 1				Model 2			
Dependent variable:	**Amount Raised (log)**							
	B	**(S.E.)**	**p-value**		**B**	**(S.E.)**	**p-value**	
(Constant)	.178	(6.493)	.978		–.689	(6.652)	.918	
Control Variables: Campaign Characteristics								
Duration	–.003	(.011)	.784		–.004	(.012)	.755	
Hardcap (log)	.650	(.188)	.001	**	.697	(.196)	.001	**
ICO Price (log)	.004	(.226)	.987		.037	(.245)	.880	
Presale Program	.086	(.426)	.842		–.223	(.475)	.641	
Bounty Program	.642	(.608)	.297		.766	(.639)	.238	
Airdrop Program	–.511	(.400)	.209		–.396	(.411)	.341	
Referral Program	.308	(.344)	.376		.242	(.354)	.499	
Token Retention	.567	(1.889)	.765		1.018	(1.967)	.608	
Cryptocurrencies Only	–.183	(.586)	.765		.053	(.668)	.937	
Control Variables: Venture Characteristics								
Established Start-up	.090	(.725)	.902		.198	(.749)	.793	
Team Size	.803	(.208)	.000	***	.758	(.213)	.001	**
Advisor Size	.005	(.036)	.896		.011	(.038)	.767	
Social Media Channels	.051	(.054)	.353		.055	(.057)	.343	
Independent Variables: Signal Vehicles for Technological Capabilities								
Public Source Code					.145	(.451)	.750	
Own Blockchain					1.737	(1.666)	.304	
Patent					–.780	(.920)	.402	
Country Dummies	Included				Included			
Token Dummies	Included				Included			
No. of observations	80 ICOs				80 ICOs			
F-value	2.750 (p-value = .001)				2.570 (p-value = .002)			
R^2	.718				.735			
Adjusted R^2	.457				.448			

Notes: *** p<.001. ** p<.01. * p<.050; standard errors in parentheses.
Results for country and token dummies are not displayed for reasons of clarity.

Table 4.6: Regression Results 2018 (Study 3)

	Model 1				Model 2			
Dependent variable:	**Amount Raised (log)**							
	B	**(S.E.)**	**p-value**		**B**	**(S.E.)**	**p-value**	
(Constant)	–43.453	(23.739)	.070		–48.631	(22.859)	.036	*
Control Variables: Campaign Characteristics								
Duration	6.034	(3.755)	.946		6.136	(3.616)	.214	
Hardcap (log)	3.581	(3.565)	.044	*	4.026	(3.446)	.014	*
ICO Price (log)	2.287	(3.812)	.432		3.297	(3.684)	.385	
Presale Program	4.925	(4.491)	.573		5.180	(4.353)	.626	
Bounty Program	11.363	(4.531)	.534		11.083	(4.358)	.605	
Airdrop Program	.001	(.008)	.352		.011	(.009)	.285	
Referral Program	.690	(.339)	.917		.816	(.328)	.711	
Token Retention	–.349	(.443)	.109		–.370	(.425)	.039	*
Cryptocurrencies Only	–.668	(1.183)	.000	***	–.558	(1.142)	.000	***
Control Variables: Venture Characteristics								
Established Start-up	.168	(.851)	.844		.013	(.823)	.987	
Team Size	1.200	(.314)	.000	***	.945	(.312)	.003	**
Advisor Size	.051	(.051)	.318		.072	(.052)	.169	
Social Media Channels	.088	(.082)	.284		.080	(.084)	.345	
Independent Variables: Signal Vehicles for Technological Capabilities								
Public Source Code					2.797	(.848)	.001	**
Own Blockchain					.520	(.902)	.565	
Patent					1.091	(1.615)	.501	
Country Dummies	Included				Included			
Token Dummies	Included				Included			
No. of observations	166 ICOs				166 ICOs			
F-value	3.190 (p-value = .000)				3.500 (p-value = .000)			
R^2	.621				.661			
Adjusted R^2	.426				.472			

Notes: *** p<.001. ** p<.01. * p<.050; standard errors in parentheses.
Results for country and token dummies are not displayed for reasons of clarity.

Table 4.7: Regression Results 2019 (Study 3)

	Model 1				Model 2			
Dependent variable:	**Amount Raised (log)**							
	B	**(S.E.)**	**p-value**		**B**	**(S.E.)**	**p-value**	
(Constant)	–36.800	(9.900)	.001	**	–23.171	(9.884)	.024	*
Control Variables: Campaign Characteristics								
Duration	.000	(.003)	.966		.001	(.003)	.769	
Hardcap (log)	.581	(.227)	.014	*	.493	(.232)	.039	*
ICO Price (log)	.394	(.291)	.183		.485	(.269)	.079	
Presale Program	–.450	(.678)	.511		–.192	(.628)	.761	
Bounty Program	.093	(.770)	.905		.178	(.721)	.806	
Airdrop Program	.878	(.689)	.210		.550	(.642)	.396	
Referral Program	.082	(.711)	.908		–.395	(.678)	.564	
Token Retention	5.371	(4.328)	.221		–.136	(4.302)	.975	
Cryptocurrencies Only	.370	(.680)	.598		.261	(.725)	.721	
Control Variables: Venture Characteristics								
Established Start-up	–.779	(.643)	.232		–.751	(.594)	.213	
Team Size	.676	(.318)	.039	*	.628	(.299)	.042	*
Advisor Size	.063	(.050)	.211		.002	(.051)	.969	
Social Media Channels	.072	(.067)	.294		.078	(.065)	.233	
Independent Variables: Signal Vehicles for Technological Capabilities								
Public Source Code					1.245	(.701)	.083	
Own Blockchain					8.502	(3.180)	.011	**
Patent					.432	(1.062)	.686	
Country Dummies	Included				Included			
Token Dummies	Included				Included			
No. of observations	86 ICOs				86 ICOs			
F-value	2.650 (p-value = .001)				3.240 (p-value = .000)			
R^2	.712				.777			
Adjusted R^2	.443				.537			

Notes: *** p<.001. ** p<.01. * p<.050; standard errors in parentheses.
Results for country and token dummies are not displayed for reasons of clarity.

4.5 Discussion

4.5.1 Key Findings

The aim of our study was to investigate different signal vehicles for technological capabilities and their impact on ICO fundraising success. First, our main results show that publishing a source code is an effective signal vehicle for start-ups to signal technological capabilities to ICO investors. In doing so, ICO start-ups reveal the technical suitability and current state of the project (Adhami et al., 2018). We find that ICO investors prefer investing in such start-ups.

Second, the results suggest that developing an own blockchain is not an effective signal vehicle. This might be the case because tech-savvy ICO investors know that adapting an existing blockchain comes with programming activities because start-ups need to adjust an existing blockchain to fit their founding project (Fisch, 2019). As hundreds of blockchains exist (BitDegree, 2019), ICO start-ups could efficiently adapt one of these blockchains instead of developing an own blockchain.

Third, we find that a patent is not an effective driver of ICO fundraising success. This finding may be because ICO start-ups create a source code, i.e., they create software (Fisch, 2019). In general, patenting activities are less relevant in the context of software innovations (Fisch, 2019; Mann and Sager, 2007). Therefore, investors might not expect such a signal vehicle in the ICO context and cannot interpret it adequately (Fisch, 2019).

Zooming in on the effect of these three signal vehicles across different periods, we reveal that signal vehicles' effectiveness changes over time. Such changes characterize not only the ICO market itself (Bellavitis et al., 2021) but also the investment behavior of ICO investors. However, our results imply that ICO investors' behavior does not completely follow the typical shape as defined by diffusion theory (Rogers, 2003). This finding might be the case because the extreme hype about ICOs, especially in 2017, attracted adopters who were not familiar with the blockchain business in general and ICOs in particular. Consequently, characteristics of these adopters do not follow the classic logic of diffusion theory. In this regard, Fisch et al. (2021) demonstrate that the hype-investors from mid-2017 to mid-2018 usually had backgrounds different from those of typical ICO investors. This might explain why signaling technological capabilities was irrelevant in 2017, as investors were less driven by technological motives (Fisch et al., 2021). At that time, investor sentiment was high (Howell et al., 2020), so easier observable signal vehicles, such as specific human and social capital characteristics (e.g., An et al., 2019; Ante et al., 2018), were sufficient to convince ICO investors.

In 2018 and 2019, signal vehicles for technological capabilities became more effective in increasing ICO fundraising success. At that time, the hype of ICOs was waning, so the share of tech-savvy investors went back up and investor behavior rather followed the typical characteristics of diffusion theory (Rogers, 2003). On the one hand, publishing the source code became an effective signal vehicle when the early majority entered the market in 2018. On the other hand, developing an own blockchain turned out to be more relevant when the late majority came into the market in 2019. This finding implies that developing an own blockchain is a more easily observable signal vehicle for technological capabilities because the late majority is usually less tech-savvy than the early majority (Dedehayir et al., 2017). By contrast, ICO investors must be able to read a source code for it to be an effective signal vehicle, but the average ICO investor from the late majority is probably not able to read and understand the source code.

4.5.2 Implications for Theory

With this study, we contribute to ICO literature in several ways. First, prior research on ICO fundraising success usually concentrates on campaign (e.g., Giudici et al., 2020), venture (e.g., Chen, 2019), or technological (e.g., Howell et al., 2020) characteristics. Among these studies, researchers typically consider signal vehicles from only one or two of these categories. Going beyond that, we contribute to ICO research by examining multiple signal vehicles for technological capabilities while also accounting for several campaign and venture characteristics. In addition, we draw on a sample that includes ICOs from 2014 to 2020, while prior research usually considers ICOs up to 2018 or 2019. We are therefore able to create a more comprehensive and realistic picture of the drivers of ICO fundraising success.

Second, we add knowledge to ICO research in terms of technological characteristics. Most studies in this area of research concentrate on the source code of ICO start-ups. In this context, we contribute to the ongoing discussion of whether the publication of source code contributes to ICO fundraising success or not (e.g., Adhami et al., 2018; Fisch, 2019). In contrast with most previous studies, we not only concentrate on GitHub as a means to publish the source code (e.g., Fisch, 2019; Howell et al., 2020) but also widen the publication form to white papers and websites to better mirror reality. Consequently, we provide stronger evidence that publishing the source code indeed is a signal of technological capabilities that attracts investors (Adhami et al., 2018).

We further contribute to the research stream of technological characteristics in ICO research by examining two additional signal vehicles for technological capabilities. On the one hand, we introduce the signal vehicle of developing an own blockchain. In terms of the underlying blockchain, prior studies usually examine how the use of the Ethereum blockchain influences ICO fundraising success but find inconclusive results (e.g., Fisch, 2019; Giudici et al., 2020). We go beyond these insights by revealing that developing an own blockchain does not generally increase ICO fundraising success as compared with adapting an existing blockchain. In this regard, we widen the focus of research beyond Ethereum. This approach allows us to provide more wide-ranging conclusions about the choice of the underlying blockchain because we concentrate on not just one specific blockchain but two essentially different approaches of ICO start-ups to select the technological foundation for their founding projects. This insight is essential because deciding to develop an own blockchain or adapting an existing blockchain is one of the first choices for ICO start-ups in the founding process. On the other hand, we examine the signal vehicle of having a patent. In this regard, we confirm the finding of Fisch (2019) that patents do not increase ICO fundraising success. Thus, we conclude that patents do not play an important role as a signal vehicle for technological capabilities for ICO investors. With this finding, we prove the argument that ICO investors differ from more established players in entrepreneurial finance, such as venture capitalists, who prefer investing in start-ups that own patents (e.g., Baum and Silverman, 2004).

Third, research on ICO fundraising success finds inconclusive results regarding several potentially effective signal vehicles (i.e., success drivers). For example, some scholars disagree that publishing the source code increases ICO fundraising success (e.g., Adhami et al., 2018; Fisch, 2019). These disagreements might arise because studies analyze the same variables for different periods. We ascribe these inconclusive results to the fact that rapid changes affect the ICO market (Bellavitis et al., 2021). By introducing the logic of diffusion theory (Rogers, 2003) to the ICO context and conducting separate linear regressions for 2017, 2018, and 2019, we reveal that behaviors of investors vary as well. We demonstrate that ICO investors followed typical characteristics defined by diffusion theory after the hype about ICOs diminished in 2018. We come to this conclusion because the late majority, which is less tech-savvy than the early majority (Dedehayir et al., 2017), requires more easily observable signal vehicles for technological capabilities.

Finally, beyond these specific conclusions for ICO research, our study also contributes to research on signaling in general. We are the first to demonstrate that the effectiveness of signal vehicles is not constant over time, which is an important implication for signaling research. Our findings imply that the widely accepted knowledge on the effectiveness of specific signal vehicles or signals might not be robust over time but depend instead on specific developments of the corresponding market and changes that affect the market over time.

4.5.3 Implications for Practice

We derive guidelines for start-ups that are planning to conduct an ICO. Overall, start-ups more likely achieve ICO fundraising success when signaling their technological capabilities. Specifically, we show that publishing the source code is an effective signal vehicle for start-ups to demonstrate their technological capabilities to investors. Here, it is also important for ICO start-ups to ensure the technical suitability of the source code. Because experts often publicly review source codes (Roosenboom et al., 2020), a lack of technical suitability could generate a negative buzz, which would decrease ICO fundraising success. To ensure this technical suitability, we advise start-ups to hire experienced programmers to create a high-quality source code, as such a source code enhances ICO fundraising success even further (Fisch, 2019).

Nevertheless, we acknowledge that the relevance of a public source code for ICO fundraising success diminished in the last years while another signal vehicle for technological capabilities became more relevant. Thus, we advise start-ups to develop their own blockchain to signal their technological capabilities to ICO investors. In this regard, start-ups should clearly define the demands of the founding project beforehand to develop the blockchain in a way that meets these demands. In doing so, start-ups can further prove the technical suitability of the founding project's underlying technology (i.e., the blockchain).

Finally, we advise ICO start-ups not to waste their time and money on applying for a patent because these efforts do not increase ICO fundraising success. Instead, start-ups should make use of the open-source culture in the ICO context (Adhami et al., 2018) and follow the idea of decentralization, which is the core of blockchain technology and ICOs (Giudici and Adhami, 2019).

4.5.4 Limitations and Future Research

This study has some limitations that provide promising avenues for future research. First, we collected data on ICOs by drawing a random sample from a list of all ICOs. Although random sampling is a common approach to make data acquisition manageable (e.g., Bradonjic et al., 2019), we also acknowledge that this shortcut has its limitations. Above all, sample selection bias might affect our results because we had to exclude some ICOs from the random sample because of insufficient data availability (Berk, 1983). Therefore, future research should replicate our study by examining alternative random samples or, ideally, the basic population to reduce the potential for sample selection bias.

Extending the sample size would also help overcome our study's second limitation: We were unable to conduct separate analyses for all years. Nevertheless, we were able to detect notable changes in technological drivers of ICO fundraising success for 2017, 2018, and 2019. Considering these first and promising insights, we call for further research on the development of signal vehicles' effectiveness in the ICO market, as well as other forms of entrepreneurial finance, over time.

Third, this study concentrates on the effectiveness of signals in ICO fundraising. We focus on data at the ICO level but not the investor level. Given our study's findings, we call for research that dives deeper into the interpretation of signal vehicles from an investor perspective. Thus, future research should conduct interviews among ICO investors to analyze how they interpret specific signal vehicles.

Finally, this study concentrates on ICOs because this fundraising method experienced the most notable rise in the last few years (Bellavitis et al., 2021). However, other forms of token sales, such as security token offerings and initial exchange offerings, have also recently emerged (Block et al., 2020; Giudici and Adhami, 2019). Therefore, future research should reproduce our approach and examine the effectiveness of signal vehicles for technological capabilities in the context of security token offerings and initial exchange offerings.

5 General Discussion

This chapter presents a summary of the dissertation as well as an overarching discussion of implications for theory, implications for practice, and limitations, which provide important avenues for future research.

5.1 Summary

The overall aim of this dissertation is to advance knowledge by understanding equity investments as a two-sided matching model (Sørensen, 2007). According to this model, equity investments are mutual decisions so that both parties (i.e., start-ups and equity investors) have to approve this relationship (Sørensen, 2007). On the one hand, start-ups approve this relationship by selecting an equity investor based on the advantages that the equity investor can provide. On the other hand, equity investors carefully select start-ups and usually observe signals in this selection process to evaluate the quality of the start-up. This dissertation provides important findings for both of these sides.

Study 1 (Chapter 2) concentrated on the first side of the matching model by following the aim to examine if equity investors affect the survival chances of their investees and under which conditions these effects vary. Drawing on agency theory (Jensen and Meckling, 1976), I argued that different types of equity investors pursue different goals, which are more or less congruent with the goals of start-ups. In this context, goal congruence is essential for investment relationships because these relationships only become effective when the goals of equity investors and start-ups are congruent (Arthurs and Busenitz, 2003), thus leading to increased survival chances of start-ups. Additionally, I argued that start-up age and investor syndication determine goal congruence because goals change along the start-up lifecycle and goals diverge in syndicates of different types of equity investors. To test these assumptions, I analyzed a sample of 33,874 US-based start-ups via logistic regressions. The results suggested that business angels increase their investees' survival chances; by contrast, venture capitalists and corporate venture capitalists are less beneficial for their investees. I also demonstrated that the impacts of all three types of equity investors change along the start-up lifecycle. Business angels are especially beneficial in the later stages; meanwhile, corporate venture capitalists increase start-up survival chances only in the early years, and venture capitalists are less destructive in the early years. In addition, the results suggested that the effectiveness of syndicates depends on the configurations of these syndicates. Taken together, these results indicated that start-ups need to be careful in their selection of their investors because such decisions determine their survival chances.

Study 2 (Chapter 3) focused on the second side of the matching model while concentrating on venture capital as the most prevalent traditional form of start-up financing. The aim of this study was to delve deeper into the signaling effect of knowledge, which is widely acknowledged by research as a means of attracting venture capitalists (e.g., Baum and Silverman, 2004; Mann and Sager, 2007). Based on the logic of context effects theory (Whetten, 2009), I argued that contextual factors on the regional level affect how venture capitalists interpret signals because contextual factors can, for example, set a reference standard (Schwarz and Bless, 2007). To test if regional contextual factors affect the signaling effect of knowledge, I examined a sample containing 180,952 observations of 46,379 high-tech start-ups from 2005 until 2014, which were nested in 402 German regions. The results of a longitudinal multilevel analysis revealed that the geographical accessibility of a region strengthens and the knowledge stock of a region weakens the signaling effect of the start-up's knowledge stock. In sum, these findings implied the need for start-ups to be aware of regional circumstances as they pursue venture capitalists because such conditions can enhance or impair their chances to convince these equity investors.

Study 3 (Chapter 4) was also pertinent to the second side of the matching model, but its focus shifted towards the modern forms of start-up financing. To be precise, ICOs as a modern form of start-up financing constituted the focal point of Study 3 because ICOs recorded the most notable development in recent times (Bellavitis et al., 2021). Prior research finds that signaling is also relevant in the ICO context to reduce information asymmetries (Momtaz, 2020a). In this context, signals of technological capital should play a key role because ICOs are embedded in a technology-driven environment (Fisch, 2019). However, research is scarce and it provides ambiguous results thus far regarding the signals of technological capital (e.g., Adhami et al., 2018; Fisch, 2019). Hence, Study 3 aimed at delving more deeply into signaling technological capital in the ICO context. Drawing on signaling theory (Spence, 1973), I derived three vehicles that should signal the technological capital of a start-up, namely publishing the source code, developing an own blockchain, and having at least one patent. I analyzed a sample of 357 ICOs and found that an ICO becomes more successful when the start-up published the source code. Through separate analyses for three years, the results also showed that the effectiveness of signals changes over time because ICO investors, to some extent, behave like adopters of innovations (Rogers, 2003). Taken together, Study 3 suggested that specific strategies are available for start-ups to attract ICO investors by signaling their technological capital; however, these strategies can change over time based on the developments of the ICO market.

5.2 Implications for Theory

Beyond each study's specific implications for theory, which I previously discussed in the respective chapters (Chapters 2 – 4), this dissertation in its entirety contributes to research on start-up financing as well.

First, prior research usually focuses on one side of the two-sided matching model; it either explores how equity investors affect their investees (e.g., Bonini et al., 2019; Engel and Keilbach, 2007) or how start-ups can attract equity investors (e.g., Baum and Silverman, 2004; Fisch, 2019). Going beyond these studies, this dissertation follows the logic of start-up financing as a two-sided matching model (Sørensen, 2007). Consequently, this dissertation is able to adopt both perspectives defined by Sørensen (2007): start-ups selecting equity investors and vice versa. Therefore, I am able to answer both questions "Who are the right equity investors for start-ups?" (Chapter 2) and "How can start-ups attract equity investors?" (Chapters 3 and 4); on the contrary, existing studies answer only one of these two questions. Thus, this dissertation depicts a more comprehensive and realistic picture than existing studies in this research field.

In addition, this dissertation delves even deeper into the question "How can start-ups attract equity investors?" by examining both traditional (Chapter 3) and modern (Chapter 4) forms of start-up financing. In this regard, existing studies usually concentrate on either traditional (e.g., Franke et al., 2008; Zhang et al., 2019) or modern (e.g., Adhami et al., 2018; Ante et al., 2018) forms of start-up financing. On the one hand, research on the effectiveness of signals for traditional forms of start-up financing, including venture capital, is very extensive. Nevertheless, calls for research to advance this research field continue. For example, Colombo (2021) concludes that contextual factors play an important but under-researched role for the effectiveness of signals. Additionally, scholars demand more advanced empirical approaches in entrepreneurship research to enhance the quality of implications (e.g., Anderson et al., 2019; Shepherd, 2011). By considering a regional perspective and conducting a multilevel analysis, this dissertation follows both calls for research and provides new and more reliable insights into an established research field. On the other hand, markets for start-up financing are highly dynamic and multiple new forms of start-up financing have emerged, such that research on this topic is still in its start-up phase. Thus, numerous calls for research on new players in start-up financing have been made recently (e.g., Bellavitis et al., 2016; Block et al., 2018a; Block et al., 2020). By concentrating on corporate venture capitalists and ICOs as such modern forms (Block et al., 2018a), this dissertation makes a step towards answering these calls and advancing this nascent stream of research. Taken together, this dissertation combines these two perspectives of modern and traditional forms of equity investments, thus providing a comprehensive overview on the different start-up financing forms that are available to start-ups.

5.3 Implications for Practice

Each of the three studies of this dissertation provides specific implications for practice, which I previously discussed in the corresponding chapters. Going beyond these specific implications, I derive additional overarching implications for practice in this chapter.

First, this dissertation offers important insights for start-ups that are attempting to close their funding gaps through equity investments. This dissertation posits that start-ups have to judiciously select their equity investors and helps start-ups in terms of the means of attracting various types of equity investors. On the one hand, I reveal that actively involved equity investors such as venture capitalists (Colombo and Grilli, 2010) bear the risk of conflicting interests that have a negative impact on the development of start-ups. Thus, start-ups might consider to pursue modern forms of start-up financing such as ICOs or crowdfunding (Block et al., 2018a). The investment approaches of these modern forms of start-up financing are passive (Block et al., 2018a), such that the risk of conflicting interests is lower or even non-existent.

After deciding to pursue a specific type of equity investor, the start-up should send signal vehicles to reduce information asymmetries, which adversely affect equity investors (Connelly et al., 2011). In this regard, the start-ups' possibilities to send signal vehicles to equity investors are manifold. For example, start-ups should focus on signaling their intellectual (e.g., Hsu and Ziedonis, 2013; Lahr and Mina, 2016), social (e.g., Hoenig and Henkel, 2015; Hsu, 2007), and human (e.g., Baum and Silverman, 2004; Ko and McKelvie, 2018) capital to convince equity investors of their investment worthiness. However, this dissertation highlights the need for start-ups to recognize the regional context and developments of the corresponding financial market because these aspects can alter the way that equity investors interpret specific signal vehicles. For example, start-ups should decide for a signal vehicle and observe the average manifestation of this signal vehicle among start-ups in their regional surroundings because equity investors can use this regional information as reference standard for evaluating a start-up (Schwarz and Bless, 2007).

Second, equity investors can learn from this dissertation. On the one hand, this dissertation provides insights in terms of how equity investors should shape the investment relationships with their investees. Before equity investors invest, they should observe the age of a potential investee and reflect upon any intent to syndicate with other types of equity investors. On the other hand, this dissertation helps equity investors to understand their own investment decisions. For example, venture capitalists often lack an understanding of their own decision processes because of an information overload (Zacharakis and Meyer, 1998). For other start-up financing types such as ICOs and crowdfunding, these problems should also prevail because private investors are primarily active in these financing contexts (Ahlers et al., 2015; Huang et al., 2019). Information overload might affect these unprofessional investors even more than venture capitalists. Overall, this dissertation helps equity investors to understand their own investment decisions and reveals that contextual factors are an additional source of information, which unconsciously affect the investment decisions of equity investors. The equity investors' greater awareness of their own decisions should lead to greater success because they can consciously improve their decision processes (Zacharakis and Meyer, 1998).

Finally, this dissertation provides guidance for policymakers who intend to spur entrepreneurial activities in their sphere of influence. The development of entrepreneurial clusters is often based on the availability of venture capital in specific regions (Cumming and Dai, 2010; Florida and Kenney, 1988). However, this dissertation helps policymakers in terms of the manner of shaping these clusters. On the one hand, my findings suggest that policymakers should not merely focus on building entrepreneurial clusters around venture capitalists because this approach can backfire in the long term due to the low survival rates of venture capital-financed start-ups located in such clusters. For example, policymakers should also attract business angels to spur entrepreneurial clusters in the long term. To do so, policymakers could provide financial subsidies to business angels that invest in start-ups located in the cluster. Thus, business angels have more money to work with when they act as active investors. As a result, these equity investors can stimulate the development of their investees and advance the entire entrepreneurial cluster.

Additionally, policymakers should support start-ups that are located within the entrepreneurial cluster. On the one hand, policymakers could provide governmental venture capital, which is an effective signal to attract equity investors that provide follow-up funding (Colombo et al., 2016). On the other hand, policymakers could follow a less money-intensive approach to support start-ups by, for example, hosting workshops for start-ups in terms of how to attract different types of equity investors. Based on the knowledge from this dissertation and prior research, these workshops would help start-ups to find the "right" equity investors and learn how to attract this equity investor via signaling. In these workshops, policymakers should make the start-ups also aware of the fact that the effectiveness of signals depends on regional factors and market developments. For example, policymakers should teach start-ups to emphasize signal vehicles that help start-ups to differentiate themselves from others in that cluster.

5.4 Limitations and Future Research

This dissertation considers multiple perspectives and thus provides novel insights into both traditional and modern forms of start-up financing; nonetheless, it has some limitations that open up promising avenues for future research. For example, this dissertation mainly examines samples from Western economies, such as the US and Germany, which is in line with the majority of studies on start-up financing (e.g., Haeussler et al., 2014; Park and Steensma, 2012). Study 1 considers a sample of US-based start-ups, whereas Study 2 draws on a sample of German high-tech start-ups. Although the sample of Study 3 examines ICOs from around the world, we also observe a slight bias towards Western economies because most ICO start-ups in the sample are located in the US or the UK. Given this focus on Western economies, the generalizability of the findings of this dissertation might be debatable to some extent. For example, by drawing on institutional theory, prior research has shown that the goals and activities of venture capitalists can differ between venture capitalists in Eastern and Western economies (Ahlstrom and Bruton, 2006; Bruton and Ahlstrom, 2003). Therefore, future research should replicate the approaches of this dissertation by concentrating on Eastern economies to test the generalizability of the dissertation's findings.

Furthermore, Study 2 indirectly and Study 3 directly draw signaling theory to argue for specific relationships between signals and fundraising success. Signaling theory states that signal vehicles need to fulfill two conditions to be effective: they have to be observable to outsiders and costly to realize for insiders (Schuhmacher et al., 2018; Spence, 1973). This dissertation strictly follows these conditions and concentrates only on costly signal vehicles such as patents. However, a nascent stream of research argues that costless signal vehicles are also available, such as positive language usage and statements about future goals, which can positively or negatively affect fundraising success (e.g., Anglin et al., 2018; Di Pietro et al., 2020). In line with the future research agenda of Colombo (2021), I advise research to advance knowledge on such costless signal vehicles. Future research should investigate how different types of equity investors perceive these costless signal vehicles and if contextual factors, including a regional component, determine the equity investors' interpretation of these costless signal vehicles.

Moreover, this dissertation provides answers to two questions: (1) “Who are the right equity investors for start-ups?” and (2) “How can start-ups attract equity investors?” Although this dissertation can answer the second question for both traditional and modern forms of start-up financing, it does not provide insights into how modern forms of start-up financing, including ICOs and crowdfunding, affect the long-term survival of start-ups. In other words, I cannot conclude whether these forms of start-up financing are a sensible fundraising approach for start-ups in the long term. Due to the novelty of these fundraising methods, especially in the case of ICOs, I was unable to collect data regarding the long-term survival of these start-ups. Similarly, prior research does not provide insights into the impact of modern forms of start-up financing on long-term survival yet, but it only offers brief insights into their short-term survival (e.g., Bento et al., 2019; Yen et al., 2021). Therefore, I advise future research to verify whether modern forms of start-up financing have a positive or a negative impact on the survival chances of start-ups in the long term to derive additional implications for both start-ups and equity investors.

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Appendices

Table A1: Literature Overview – Venture Capitalists' Impact on their Investees

Study	Start-ups' Development	Sample	Key Findings
Bernstein et al. (2016)	• Innovation performance • Exit	22,986 companies receiving funding from 3,158 venture capital firms (USA)	Airline routes, which reduce travel times, enable venture capitalists to increase on-site involvement. This greater on-site involvement boosts innovation and the likelihood of a successful exit.
Bertoni et al. (2011)	• Growth	538 new technology-based firms (Italy)	Venture capital-financed high-tech start-ups exhibit significantly higher growth. This effect is especially strong immediately after the first financing round.
Bruton et al. (2010)	• IPO performance	224 IPOs (UK and France)	Venture capital ownership negatively affects IPO performance.
Chen (2009)	• Financial performance	122 start-ups (location not specified)	Venture capitalists' involvement influences the relationship between technology commercialization and new venture performance. However, venture capital support lacks a general effect on performance.
Dimov and De Clercq (2006)	• Failure	200 venture capital firms (USA)	Venture capitalists with relevant knowledge in the specific situation have portfolios with lower failure rates. However, syndication among venture capitalists increases this failure rate.
Engel and Keilbach (2007)	• Firm growth • Innovation performance	21,375 non-venture capital-funded and 142 venture capital-funded start-ups (Germany)	Venture capital-funded start-ups exhibit higher growth rates. However, innovation performance does not differ between venture capital-funded and non-venture capital-funded start-ups.
Jelic et al. (2005)	• Financial performance	167 management buy-outs through IPOs (UK)	In general, venture capital-funded management buyouts do not perform better or worse than non-venture capital-funded management buyouts. However, the involvement of reputable venture capitalists increases performance.
Johnson and Sohl (2012)	• Financial performance	799 IPOs (USA)	Venture capital-financed IPO firms do not perform better than non-venture capital-financed IPO firms. Moreover, complementarities occur between business angels and venture capitalists.
Kelly and Kim (2018)	• Growth	662 venture capital-financed and 662 non venture capital-financed firms (Canada)	Firms financed by venture capitalists grow faster than propensity-matched firms, which are not financed by venture capitalists.
Manigart et al. (2002)	• Survival	565 venture capital-funded and 565 non-venture capital-funded start-ups (Belgium)	Venture capital-funded start-ups have a lower likelihood of survival than comparable non-venture capital-funded start-ups. However, specific venture capitalists are able to increase the probability of survival.
Nahata (2008)	• Exit • Productivity	33,539 venture capital investments (USA)	Start-ups financed by reputable venture capitalists are more likely to exit successfully and at a faster rate; their productivity is also greater.

Table A1: Literature Overview – Equity Investors' Impact on their Investees (cont.)

Study	Start-ups' Development	Sample	Key Findings
Nanda and Rhodes-Kropf (2013)	• Bankruptcy • Firm value • Innovation performance	12,285 venture capital-funded start-ups (USA)	Start-ups financed by venture capitalists in hot markets exhibit a higher probability of bankruptcy, but valuation at the day of the IPOs and innovation performance are greater. Furthermore, start-ups financed earlier are less likely to become bankrupt.
Ragozzino and Blevins (2016)	• Exit	3,566 start-ups (USA)	The prominence of venture capitalists increases exit via IPO, and it does not affect exit via acquisition. The number of venture capitalists investing in a start-up is a driver of exit via acquisition but not via IPO. The time of venture capitalists' investment decreases exit chances via acquisition and IPO. Finally, the total amount invested by venture capitalists increases exit via IPO but not via acquisition.
Rosenbusch et al. (2013)	• Firm growth • Profitability • Stock market performance	76 empirical samples on 36,567 firms (worldwide)	The meta-analysiscal shows that venture capital invest-ments have a small but positive impact on the growth and stock-market performance of firms but have no significant effect on profitability. However, the positive effects are not robust for start-up samples.
Sapienza (1992)	• Financial and non-financial performance	Matched responses from CEOs and lead venture capitalists of 51 start-ups (USA)	The involvement of venture capitalists increases start-up performance.
Stubner et al. (2007)	• Financial performance	106 start-ups (Germany)	Venture capitalists' management support positively affects start-ups' performance. The characteristics of the founder team and the start-up do not affect this main relationship.

Table A2: Literature Overview – Corporate Venture Capitalists' Impact on their Investees

Study	Start-ups' Development	Sample	Key Findings
Chemmanur et al. (2014)	• Innovation performance • Profitability	462 corporate venture capital-funded and 1,667 venture capital-funded start-up IPOs (location not specified)	Start-ups financed by corporate venture capitalists are more innovative but less profitable than start-ups financed by (independent) venture capitalists.
Gompers and Lerner (2000b)	• Firm value	32,364 investments in 8,506 funding rounds (location not specified)	Start-ups financed by corporate venture capitalists are at least as successful as start-ups financed by independent venture capitalists. This case is especially true if a strategic fit exists between the start-up and the investor.
Huang and Madhavan (2020)	• Technological performance • Exit • Financial performance	68 empirical samples on 33,613 firms (worldwide)	The meta-analysis indicates that corporate venture capital investments increase the investees' chances for successful exit and financial performance. However, corporate venture capital investments negatively affect the investees' technological performance.
Ivanov and Xie (2010)	• Firm value	3,020 IPOs financed by (corporate) venture capital (location not specified)	IPOs funded by corporate venture capitalists undergo higher valuations than IPOs without financing or are financed by (independent) venture capitalists.
Kang (2019)	• Exit	1,121 start-ups who received funding by corporate venture capitalists and venture capitalists (USA)	Start-ups that receive funding from corporate venture capitalists and venture capitalists are less likely to conduct a successful exit when the corporate venture capitalist is more influential than the venture capitalist.
Park and Bae (2018)	• Innovation performance	762 venture capital-financed biotechnology start-ups (USA)	The innovation performance of corporate venture capital-financed start-ups is not higher than that of venture capital-financed start-ups. However, corporate venture capital-financed start-ups perform better in terms of innovations when they received funding later.
Park and Steensma (2012)	• Exit • Failure	508 start-ups financed by (corporate) venture capitalists (USA)	Investments by corporate venture capitalists increase both the likelihood of a successful exit and the probability of failure. Corporate venture capitalists are especially valuable if start-ups require specialized complementary assets.

Table A3: Literature Overview – Business Angels' Impact on their Investees

Study	Start-ups' Development	Sample	Key Findings
Bonini et al. (2019)	• Performance • Survival	111 business angel-financed start-ups (Italy)	Start-ups perform better and are more likely to survive when they are financed by a syndicate of business angels. However, a high intensity of business angels' monitoring can become detrimental for start-ups.
Bruton et al. (2010)	• Financial performance	224 IPOs (UK and France)	Business angel ownership positively affects IPO performance.
Collewaert and Sapienza (2016)	• Innovation performance	54 teams of business entrepreneurs and business angels (Belgium and USA)	Conflicts between business angels and start-ups decrease start-up performance. This effect becomes stronger if the teams have lower levels of agreement on priorities, less diverse experience, and communicate more frequently.
Croce et al. (2018)	• Exit • Subsequent funding	1,933 high-tech start-ups financed by business angels (worldwide)	Business angels with early-stage experience increase the subsequent funding, whereas business angels with later-stage experience boost the likelihood of a successful exit. Furthermore, sequential and co-investment of business angels and venture capitalists increases both the subsequent funding and the probability of a successful exit.
Johnson and Sohl (2012)	• Financial performance	799 IPOs (USA)	Business angel-financed IPO firms do not perform better than non-angel-financed IPO firms. Moreover, complementarities exist between business angels and venture capitalists.
Kerr et al. (2014)	• Exit • Survival • Growth • Subsequent funding	130 start-ups (USA)	Start-ups financed by business angels grow faster and are more likely to survive and exit successfully. However, the subsequent funding is lower for such start-ups.
Levratto et al. (2018)	• Growth	432 business angel-financed firms (France)	The authors find mixed results regarding the impact of business angels on their investees' growth. Business angel-financed firms perform better in comparison to a random sample but similar to a nearest neighbor sample.

Table A4: Literature Overview – Signals in Venture Capital

Study	Signals	Sample	Key Findings
Baum and Silverman (2004)	• Intellectual capital • Social capital • Human capital	204 biotechnology start-ups (Canada)	Intellectual capital increases venture capital investments. However, the results regarding alliance and human capital are inconclusive, as they only partly increase venture capital investments.
Block et al. (2014)	• Intellectual capital	13,269 funding rounds of 2,671 start-ups (USA)	The number and breadth of trademarks increase venture capital evaluations until a certain point (inverted u-shaped relationship).
Block et al. (2014)	• Intellectual capital	50,596 funding rounds of 2,341 start-ups (USA)	The presence of a trademark has a positive impact on venture capital valuations. The number of trademarks also has a positive effect, but this effect turns around when a start-up possesses too many trademarks.
Chen et al. (2009)	• Organizational capital	159 evaluations of business plan presentations by venture capitalists (location not specified)	On the one hand, organizational capital in terms of preparedness does increase venture capital funding. On the other hand, organizational capital in terms of entrepreneurial passion cannot attract venture capital funding.
Franke et al. (2008)	• Human capital	51 conjoint experiments (Germany and Austria)	Industry and leadership experience as well as the education of the start-up team increase the evaluations of venture capitalists. Human capital signals are more important from the perspective of novice venture capitalists; by contrast, experienced venture capitalists prefer team cohesion.
Haeussler et al. (2014)	• Intellectual capital	190 biotech start-ups (Germany and UK)	Patent applications, citations, and oppositions reduce the time until the first venture capital investment, whereas granted patents do not.
Hoenen et al. (2014)	• Intellectual capital	580 biotechnology firms (USA)	Patent applications increase venture capital funding, but this effect diminishes after the initial investment.
Hoenig and Henkel (2015)	• Intellectual capital • Social capital • Human capital	187 venture capitalists (USA and Europe)	Social and human capital have a positive signaling value on venture capitalists. Intellectual capital attracts venture capitalists by its property rights function but not by its signaling effect.
Hsu (2007)	• Social capital • Human capital	149 early stage technology based start-ups (USA)	Human capital increases both the venture evaluation and the likelihood to receive venture capital. Moreover, social capital positively influences the venture valuation.
Hsu and Ziedonis (2013)	• Intellectual capital	370 semiconductor start-ups (USA)	Patent applications increase the start-ups' valuations from the perspective of venture capitalists.
Kirsch et al. (2009)	• Organizational capital • Human capital	722 funding requests (USA)	Information provided in a business plan (i.e., organizational capital) are rather ineffective signals that only marginally increase venture capital investments. Specifically, the scholars analyze human capital signals in this context and find no significant signaling effect.

Table A4: Literature Overview – Signals in Venture Capital (cont.)

Study	Signals	Sample	Key Findings
Ko and McKelvie (2018)	• Human capital	235 start-ups (location not specified)	Signaling human capital through founding experience and education positively affect first-round financing, but this effect only remains robust for education in later financing stages. Furthermore, the effect of founding experience becomes positive in later rounds when investor prominence is high.
Lahr and Mina (2016)	• Intellectual capital	940 start-ups (UK and USA)	Start-ups that have at least one patent application or a patent grant are more likely to receive venture capital.
Mann and Sager (2007)	• Intellectual capital	722 funding rounds in 221 software start-ups (location not specified)	Both the number of patents and ownership of any patent increase the number of funding rounds and the total amount of financing by venture capitalists.
Patzelt (2010)	• Human capital	117 funding rounds in biotechnology start-ups (Europe and USA)	Human capital in terms of founder-based firm-specific experience and international experience leads to higher venture capital investments in start-ups. However, management education and industry-specific experience do not affect venture capital investments. The study further finds that the effect of human capital varies by team size.
Zhang et al. (2019)	• Intellectual capital	535 venture capital investments in 457 bio-pharmaceutical start-ups (China)	This study differentiates the signaling value of patents in terms of legal, technological, and commercial signals. The findings reveal that legal and technological patent signals increase venture capital financing; meanwhile, commercial patent signals are less beneficial.
Zhou et al. (2016)	• Intellectual capital	427 funding rounds of 299 start-ups (worldwide)	Both patents and trademarks directly increase venture capital investments. Furthermore, a complementary effect exists between patents and trademarks.

Table A5: Literature Overview – Signals in Crowdfunding

Study	Signals	Sample	Key Findings
Ahlers et al. (2015)	• Intellectual capital • Social capital • Human capital	104 crowdfunding projects (Australia)	Human capital positively affects crowdfunding success, whereas social capital and intellectual capital have no effect.
Barbi and Mattioli (2019)	• Social capital • Human capital	521 crowdfunding projects (UK)	Social capital in terms of social media usage is not a driver of crowdfunding success. Moreover, human capital in terms of a larger team and professional experience positively affects the amounts raised in crowdfunding; meanwhile, experience in the field is less relevant.
Bi et al. (2017)	• Organizational capital	1,407 crowdfunding projects (China)	Signaling preparedness through videos and extensive project introductions positively affects investment decisions.
Block et al. (2018b)	• Organizational capital	71 crowdfunding projects (Germany)	Signaling preparedness through frequent updates increases investments.
Courtney et al. (2017)	• Human capital • Organizational capital	267,295 crowdfunding projects (USA)	The founder's human capital (i.e., prior crowdfunding success) and preparedness (i.e. use of media such as videos) increase the probability of funding success.
Lukkarinen et al. (2016)	• Social capital • Human capital	60 crowdfunding projects (Finland)	Crowdfunders attach importance to other signals compared to traditional equity financiers. Human capital signals are less important in the crowdfunding context, whereas social capital signals are more important.
Mollick (2014)	• Social capital • Organizational capital	48,526 crowdfunding projects (USA)	Social capital in terms of the founder's personal networks leads to higher funding success. Additionally, organizational capital in terms of project quality and preparedness (i.e. use of media and avoidance of spelling errors) increases investments.
Piva and Rossi-Lamastra (2018)	• Human capital	284 crowdfunding projects (Italy)	Crowdfunding campaigns are more likely to succeed when the founder signals human capital through business education and entrepreneurial experience. Industry-related education and other education have no impact on crowdfunding success.
Skirnevskiy et al. (2017)	• Social capital	106 crowdfunding projects (USA)	Internal social capital through a project track record results in more successful crowdfunding projects.
Troise et al. (2020)	• Human capital • Organizational capital	509 crowdfunding projects (USA, UK, and Germany)	A larger team signals human capital, thus leading to greater success in equity-based crowdfunding. Furthermore, having organizational capital in the form of a finished business plan increases success in equity-based crowdfunding. These signals are irrelevant in reward-based crowdfunding.
Vismara (2018)	• Intellectual capital • Human capital	132 crowdfunding projects (UK)	Patents attract sophisticated and early investors, whereas larger teams attract late investors in crowdfunding.

Table A6: Literature Overview – Signals in Initial Coin Offerings

Study	Signals	Sample	Key Findings
Adhami et al. (2018)	• Technological capital	253 ICOs (worldwide)	Signaling technological capital by publishing the source code increases ICO fundraising success; meanwhile, the existence of a white paper has no significant impact.
An et al. (2019)	• Technological capital • Social capital • Human capital	715 ICOs (worldwide)	Technological capital in terms of the existence of a white paper increases ICO fundraising success. Moreover, having real-life and digital social capital (i.e., advisors and social media use) and human capital (i.e., team size and education) increases the ICO fundraising success of start-ups.
Ante et al. (2018)	• Technological capital • Social capital • Human capital	278 ICOs (worldwide)	Start-ups are more successful in terms of ICO fundraising when they have technological capital (white paper), more real-life social capital (advisors), and human capital (team size).
Chen (2019)	• Technological capital • Social capital • Human capital	626 ICOs (worldwide)	Start-ups can boost ICO fundraising success by revealing their technological capital through publishing the source code and writing a white paper, their real-life social capital through employing advisors, and their human capital through having larger teams.
Fisch (2019)	• Technological capital	456 ICOs (worldwide)	Start-ups can signal their technological capital by publishing a high-quality source code and a technical white paper to increase ICO fundraising success.
Giudici and Adhami (2019)	• Technological capital • Social capital • Human capital	935 ICOs (worldwide)	Technological capital (i.e., a white paper and public source code), real-life social capital (i.e., advisors), and human capital (i.e., team size and team experience) increase ICO fundraising success.
Giudici et al. (2020)	• Technological capital • Social capital • Human capital	931 ICOs (worldwide)	Start-ups cannot increase ICO fundraising success by revealing their technological capital through a public source code. However, a greater degree of human capital in terms of team size and social capital in terms of the existence of an advisory board increases ICO fundraising success.
Momtaz (2020a)	• Technological capital • Social capital • Human capital	495 ICOs (worldwide)	Start-ups that possess more technological capabilities (as shown by a high-quality source code), a greater degree of digital social capital (as shown by social media usage), and a greater degree human capital (as shown by quality of the management team) increase fundraising success.
Momtaz (2020b)	• Human capital	213 ICOs (worldwide)	Human capital in terms of team size increases ICO fundraising success.
Perez et al. (2020)	• Social capital	537 ICOs (worldwide)	Digital social capital in the form of social contacts through the website or social media leads to greater ICO fundraising success.
Roosenboom et al. (2020)	• Technological capital • Human capital	630 ICOs (worldwide)	Signaling technological capital via a public source code and human capital via team size increases ICO fundraising success.

Table A7: Robustness Check for the Dependent Variable in t+1 (Study 2)

	Model 1			Model 2			Model 3		
Dependent variable:	**Number of Venture Capital Investments (log, t+1)**			**Number of Venture Capital Investments (log, t+1)**			**Number of Venture Capital Investments (log, t+1)**		
	B	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**
Constant	–.00087	(.00123 .476)	[–.00328; .00153]	.00005	(.00124 .970)	[–.00239; .00248]	.00004	(.00124 .973)	[–.00240; .00248]
Control Variables (Start-up Level)									
Firm Size	.00035	(.00009 .000)	[.00017; .00052]	.00035	(.00009 .000)	[.00017; .00052]	.00035	(.00009 .000)	[.00018; .00053]
Firm Age	–.00012	(.00004 .004)	[–.00020; –.00004]	–.00012	(.00004 .004)	[–.00020; –.00004]	–.00012	(.00004 .004)	[–.00020; –.00004]
Control Variables (Regional Level)									
Household Income	.00000	(.00000 .935)	[–.00000; .00000]	–.00000	(.00000 .869)	[–.00000; .00000]	–.00000	(.00000 .877)	[–.00000; .00000]
GDP	.00002	(.00001 .002)	[.00001; .00004]	.00000	(.00001 .752)	[–.00001; .00002]	.00000	(.00001 .751)	[–.00001; .00002]
Unemployment	.00002	(.00001 .005)	[.00000; .00003]	.00001	(.00001 .125)	[–.00000; .00002]	.00001	(.00001 .127)	[–.00000; .00002]
Independent Variables (Start-up Level)									
Firm Patents (log)				.00270	(.00046 .000)	[.00179; .00360]	.00217	(.00066 .001)	[.00088; .00346]
Independent Variables (Regional Level)									
Population Density				.00000	(.00000 .069)	[–.00000; .00000]	.00000	(.00000 .089)	[–.00000; .00000]
Patent Density				.00023	(.00009 .012)	[.00005; .00040]	.00024	(.00009 .008)	[.00006; .00042]
Interactions									
Firm Patents (log) X Population Density							.00000	(.00000 .021)	[.00000; .00000]
Firm Patents (log) X Patent Density							–.00095	(.00028 .001)	[–.00150; –.00039]
Log Likelihood	278,154.56			278,180.45			278,186.16		
Wald Chi ²	48.34 (p-value = .000)			102.77 (p-value = .000)			114.01 (p-value = .000)		
No. of Observations (No. of Regions)	134,573 (402)			134,573 (402)			134,573 (402)		

Table A8: Robustness Check for the Dependent Variable in t+2 (Study 2)

	Model 1			Model 2			Model 3		
Dependent variable:	**Number of Venture Capital Investments (log, t+2)**			**Number of Venture Capital Investments (log, t+2)**			**Number of Venture Capital Investments (log, t+2)**		
	B	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**
Constant	–.00092	(.00136 .500)	[–.00358; .00175]	–.00011	(.00139 .938)	[–.00282; .00261]	–.00011	(.00139 .935)	[–.00283; .00260]
Control Variables (Start-up Level)									
Firm Size	.00042	(.00011 .000)	[.00020; .00064]	.00042	(.00011 .000)	[.00020; .00064]	.00042	(.00011 .000)	[.00020; .00065]
Firm Age	–.00015	(.00005 .004)	[–.00024; –.00005]	–.00014	(.00005 .005)	[–.00024; –.00004]	–.00014	(.00005 .005)	[–.00024; –.00004]
Control Variables (Regional Level)									
Household Income	.00000	(.00000 .840)	[–.00000; .00000]	.00000	(.00001 .998)	[–.00000; .00000]	.00000	(.00000 .996)	[–.00000; .00000]
GDP	.00002	(.00001 .006)	[.00001; .00004]	.00001	(.00001 .564)	[–.00001; .00002]	.00001	(.00001 .564)	[–.00001; .00002]
Unemployment	.00002	(.00001 .009)	[.00000; .00003]	.00001	(.00001 .133)	[–.00000; .00003]	.00001	(.00001 .135)	[–.00000; .00003]
Independent Variables (Start-up Level)									
Firm Patents (log)				.00176	(.00050 .000)	[.00077; .00274]	.00168	(.00071 .019)	[.00028; .00308]
Independent Variables (Regional Level)									
Population Density				.00000	(.00000 .129)	[–.00000; .00000]	.00000	(.00000 .139)	[–.00000; .00000]
Patent Density				.00016	(.00010 .093)	[–.00003; .00036]	.00017	(.00010 .079)	[–.00002; .00036]
Interactions									
Firm Patents (log) X Population Density							.00000	(.00000 .378)	[–.00000; .00000]
Firm Patents (log) X Patent Density							–.00054	(.00032 .085)	[–.00116; .00008]
Log Likelihood	208,797.05			208,808.09			208,809.83		
Wald Chi ²	41.62 (p-value = .000)			62.25 (p-value = .000)			68.68 (p-value = .000)		
No. of Observations (No. of Regions)	99,094 (402)			99,094 (402)			99,094 (402)		

Table A9: Robustness Check for the Dependent Variable in t+3 (Study 2)

	Model 1			**Model 2**			**Model 3**		
Dependent variable:	**Number of Venture Capital Investments (log, t+3)**			**Number of Venture Capital Investments (log, t+3)**			**Number of Venture Capital Investments (log, t+3)**		
	B	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**
Constant	–.00148	(.00165 .368)	[–.00471; .00175]	–.00074	(.00169 .662)	[–.00404; .00257]	–.00073	(.00169 .666)	[–.00404; .00258]
Control Variables (Start-up Level)									
Firm Size	.00042	(.00016 .006)	[.00012; .00073]	.00041	(.00002 .008)	[.00011; .00071]	.00043	(.00016 .006)	[.00012; .00073]
Firm Age	–.00009	(.00007 .208)	[–.00022; .00005]	–.00009	(.00007 .212)	[–.00022; .00005]	–.00009	(.00007 .206)	[–.00022; .00005]
Control Variables (Regional Level)									
Household Income	.00000	(.00000 .649)	[–.00000; .00000]	.00000	(.00000 .723)	[–.00000; .00000]	.00000	(.00000 .719)	[–.00000; .00000]
GDP	.00002	(.00001 .014)	[.00000; .00004]	.00001	(.00001 .481)	[–.00001; .00003]	.00001	(.00001 .477)	[–.00001; .00003]
Unemployment	.00002	(.00001 .019)	[.00000; .00003]	.00001	(.00001 .318)	[–.00001; .00003]	.00001	(.00001 .329)	[–.00001; .00003]
Independent Variables (Start-up Level)									
Firm Patents (log)				.00303	(.00060 .000)	[.00185; .00420]	.00195	(.00086 .023)	[.00027; .00363]
Independent Variables (Regional Level)									
Population Density				.00000	(.00000 .024)	[.00000; .00000]	.00000	(.00000 .033)	[.00000; .00000]
Patent Density				–.00005	(.00011 .672)	[–.00027; .00017]	–.00003	(.00011 .776)	[–.00026; .00019]
Interactions									
Firm Patents (log) X Population Density							.00000	(.00000 .007)	[.00000; .00000]
Firm Patents (log) X Patent Density							–.00120	(.00038 .001)	[–.00193; –.00046]
Log Likelihood	146,471.44			146,487.03			146,492.14		
Wald Chi ²	23.30 (p-value = .000)			55.44 (p-value = .000)			65.57 (p-value = .000)		
No. of Observations (No. of Regions)	70,594 (402)			70,594 (402)			70,594 (402)		

Table A10: Robustness Check for the Independent Variable Commuter Balance (Replacing Population Density) (Study 2)

	Model 1			Model 2			Model 3		
Dependent variable:	**Number of Venture Capital Investments (log)**			**Number of Venture Capital Investments (log)**			**Number of Venture Capital Investments (log)**		
	B	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**
Constant	–.00392	(.00139 .005)	[–.00664; –.00120]	–.00323	(.00143 .024)	[–.00603; –.00043]	–.00325	(.00143 .023)	[–.00604; –.00045]
Control Variables (Start-up Level)									
Firm Size	.00054	(.00009 .000)	[.00037; .00072]	.00054	(.00009 .000)	[.00036; –.00002]	.00054	(.00009 .000)	[.00036; .00071]
Firm Age	–.00010	(.00004 .019)	[–.00017; –.00001]	–.00010	(.00004 .018)	[–.00018; .00000]	–.00010	(.00004 .018)	[–.00018; –.00002]
Control Variables (Regional Level)									
Household Income	.00000	(.00000 .054)	[–.00000; .00001]	.00000	(.00000 .071)	[–.00000; .00005]	.00000	(.00000 .070)	[–.00000; .00000]
GDP	.00004	(.00001 .000)	[.00002; .00006]	.00002	(.00002 .184)	[–.00001; .00003]	.00002	(.00002 .185)	[–.00001; .00005]
Unemployment	.00002	(.00001 .004)	[.00001; .00003]	.00002	(.00001 .011)	[.00000; .00366]	.00002	(.00001 .011)	[.00000; .00003]
Independent Variables (Start-up Level)									
Firm Patents (log)				.00263	(.00052 .000)	[.00160; .00001]	.00291	(.00057 .000)	[.00179; .00402]
Independent Variables (Regional Level)									
Commuter Balance				.00000	(.00001 .897)	[–.00001; .00060]	.00000	(.00001 .965)	[–.00001; .00001]
Patent Density				.00040	(.00010 .000)	[.00603; –.00043]	.00041	(.00010 .000)	[.00021; .00060]
Interactions									
Firm Patents (log) X Commuter Balance							.00004	(.00002 .046)	[.00000; .00008]
Firm Patents (log) X Patent Density							–.00039	(.00022 .082)	[–.00082; .00005]
Log Likelihood	333,783.68			333,804.53			333,807.07		
Wald Chi ²	81.05 (p-value = .000)			124.77 (p-value = .000)			129.91 (p-value = .000)		
No. of Observations (No. of Regions)	180,952 (402)			180,952 (402)			180,952 (402)		

Notes: Commuter balance measures the difference of inbound commuters and outbound commuters in relation to the number of all employees subject to social insurance contributions (in percent) in a region. Data source: INKAR.

Table A11: Robustness Check for the Independent Variable Venture Capital Density (Replacing Population Density) (Study 2)

	Model 1			Model 2			Model 3		
Dependent variable:	**Number of Venture Capital Investments (log)**			**Number of Venture Capital Investments (log)**			**Number of Venture Capital Investments (log)**		
	B	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**
Constant	–.00392	(.00139 .005)	[–.00664; –.00120]	–.00118	(.00144 .410)	[–.00400; .00163]	–.00119	(.00144 .406)	[–.00401; .00162]
Control Variables (Start-up Level)									
Firm Size	.00054	(.00009 .000)	[.00037; .00072]	.00053	(.00009 .000)	[.00035; .00071]	.00053	(.00009 .000)	[.00036; .00071]
Firm Age	–.00010	(.00004 .019)	[–.00017; –.00001]	–.00010	(.00004 .010)	[–.00018; –.00003]	–.00011	(.00004 .009)	[–.00019; –.00003]
Control Variables (Regional Level)									
Household Income	.00000	(.00000 .054)	[–.00000; .00001]	.00000	(.00000 .312)	[–.00000; .00000]	.00000	(.00000 .311)	[–.00000; .00000]
GDP	.00004	(.00001 .000)	[.00002; .00006]	–.00000	(.00001 .477)	[–.00003; .00001]	–.00001	(.00001 .503)	[–.00003; .00001]
Unemployment	.00002	(.00001 .004)	[.00001; .00003]	–.00001	(.00001 .184)	[–.00000; .00002]	.00001	(.00001 .183)	[–.00000; .00002]
Independent Variables (Start-up Level)									
Firm Patents (log)				.00269	(.00052 .000)	[.00167; .00372]	.00251	(.00058 .000)	[.00138; .00364]
Independent Variables (Regional Level)									
Venture Capital Density				.04499	(.00522 .000)	[.03476; .05522]	.04414	(.00522 .000)	[.03391; .05438]
Patent Density				–.00013	(.00012 .296)	[–.00037; .00011]	–.00011	(.00012 .369)	[–.00035; .00013]
Interactions									
Firm Patents (log) X Venture Capital Density							.10046	(.02589 .000)	[.04971; .15121]
Firm Patents (log) X Patent Density							–.00219	(.00055 .000)	[–.00328; –.00111]
Log Likelihood	333,783.68			333,841.17			333,849.14		
Wald Chi ²	81.05 (p-value = .000)			195.17 (p-value = .000)			211.14 (p-value = .000)		
No. of Observations (No. of Regions)	180,952 (402)			180,952 (402)			180,952 (402)		

Notes: Venture capital density refers to the number of venture capitalists located in a region in relation to the size of this region (in km²). We identified the names of 845 venture capitalists listed in the Spotfolio database. We collected the years of foundations as well as zip codes for these venture capitalists. After eliminating all venture capitalists, that were not located in Germany, the sample contained 583 venture capitalists at 670 locations. Data source: Spotfolio & INKAR.

Table A12: Robustness Check for the Independent Variable R&D Expenditure Density (Replacing Patent Density) (Study 2)

	Model 1			Model 2			Model 3		
Dependent variable:	**Number of Venture Capital Investments (log)**			**Number of Venture Capital Investments (log)**			**Number of Venture Capital Investments (log)**		
	B	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**
Constant	–.00226	(.00152 .136)	[–.00524; .00071]	–.00066	(.00151 .665)	[–.00362; .00231]	–.00064	(.00152 .673)	[–.00361; .00233]
Control Variables (Start-up Level)									
Firm Size	.00013	(.00012 .266)	[–.00010; .00036]	.00013	(.00012 .280)	[–.00010; .00035]	.00013	(.00012 .249)	[–.00009; .00036]
Firm Age	–.00013	(.00005 .013)	[–.00024; –.00003]	–.00013	(.00005 .012)	[–.00024; –.00003]	–.00013	(.00005 .012)	[–.00024; –.00003]
Control Variables (Regional Level)									
Household Income	.00000	(.00000 .319)	[–.00000; .00000]	.00000	(.00000 .546)	[–.00000; .00000]	.00000	(.00000 .546)	[–.00000; .00000]
GDP	.00002	(.00001 .009)	[.00001; .00004]	–.00000	(.00001 .568)	[–.00003; .00001]	–.00001	(.00001 .596)	[–.00003; .00002]
Unemployment	.00002	(.00001 .002)	[.00001; .00004]	.00001	(.00001 .255)	[–.00001; .00003]	.00001	(.00001 .263)	[–.00001; .00003]
Independent Variables (Start-up Level)									
Firm Patents (log)				.00325	(.00063 .000)	[.00202; .00448]	.00140	(.00088 .111)	[–.00032; .00313]
Independent Variables (Regional Level)									
Population Density				.00000	(.00000 .000)	[.00000; .00001]	.00000	(.00000 .001)	[.00000; .00000]
R&D Expenditure Density				.00000	(.00000 .313)	[–.00001; .00000]	.00000	(.00000 .198)	[–.00000; .00000]
Interactions									
Firm Patents (log) X Population Density							.00000	(.00000 .000)	[.00000; .00001]
Firm Patents (log) X R&D Expenditure Density							–.00000	(.00000 .000)	[–.00000; –.00000]
Log Likelihood	147,365.53			147,389.35			147,399.75		
Wald Chi ²	28.32 (p-value = .000)			85.38 (p-value = .000)			105.11 (p-value = .000)		
No. of Observations (No. of Regions)	71,038 (402)			71,038 (402)			71,038 (402)		

Notes: R&D expenditures measures all expenditures for R&D, which are conducted by internal research personnel for the companies' own purposes and external commissions. These expenditures are aggregated on the regional level and reported in 1,000,000 €. The corresponding data is available for the years 2005, 2007, 2009, 2011, and 2013 so that the sample of this robustness check is smaller. This variable is set into relation to the size of the district. Data source: SV Wissenschaftsstatistik GmbH.

Table A13: Robustness Check for the Independent Variable R&D Personnel Density (Replacing Patent Density) (Study 2)

	Model 1			**Model 2**			**Model 3**		
Dependent variable:	**Number of Venture Capital Investments (log)**			**Number of Venture Capital Investments (log)**			**Number of Venture Capital Investments (log)**		
	B	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**	**B**	**(S.E., p-value)**	**[95% CI]**
Constant	–.00226	(.00152 .136)	[–.00524; .00071]	–.00067	(.00151 .657)	[–.00362; .00228]	–.00065	(.00151 .668)	[–.00361; .00231]
Control Variables (Start-up Level)									
Firm Size	.00013	(.00012 .266)	[–.00010; .00036]	.00012	(.00012 .283)	[–.00010; .00035]	.00013	(.00012 .255)	[–.00010; .00036]
Firm Age	–.00013	(.00005 .013)	[–.00024; –.00003]	–.00014	(.00005 .012)	[–.00024; –.00003]	–.00013	(.00005 .011)	[–.00024; –.00003]
Control Variables (Regional Level)									
Household Income	.00000	(.00000 .318)	[–.00000; .00000]	.00000	(.00000 .542)	[–.00000; .00000]	.00000	(.00000 .544)	[–.00000; .00000]
GDP	.00002	(.00001 .009)	[.00001; .00004]	–.00000	(.00001 .653)	[–.00002; .00002]	–.00000	(.00001 .678)	[–.00002; .00002]
Unemployment	.00002	(.00001 .002)	[.00001; .00004]	.00001	(.00001 .310)	[–.00001; .00002]	.00001	(.00001 .317)	[–.00001; .00002]
Independent Variables (Start-up Level)									
Firm Patents (log)				.00325	(.00063 .000)	[.00202; .00448]	.00150	(.00088 .088)	[–.00022; .00322]
Independent Variables (Regional Level)									
Population Density				.00000	(.00000 .000)	[.00000; .00000]	.00000	(.00000 .001)	[.00000; .00000]
R&D Personnel Density				.00000	(.00001 .708)	[–.00002; .00003]	.00001	(.00001 .523)	[–.00002; .00003]
Interactions									
Firm Patents (log) X Population Density							.00000	(.00000 .000)	[.00000; .00001]
Firm Patents (log) X R&D Personnel Density							–.00018	(.00004 .000)	[–.00026; –.00009]
Log Likelihood	147,375.82			147,399.24			147,408.72		
Wald Chi ²	28.32 (p-value = .000)			86.01 (p-value = .000)			103.87 (p-value = .000)		
No. of Observations (No. of Regions)	71,042 (402)			71,042 (402)			71,042 (402)		

Notes: R&D personnel measures the aggregated amount research personnel in one region (reported in full-time equivalents). The corresponding data is only available for the years 2005, 2007, 2009, 2011, and 2013 so that the sample of this robustness check is smaller. This variable is set into relation to the size of the district. Data source: SV Wissenschaftsstatistik GmbH.

Affidavit

Ich erkläre hiermit, dass ich die vorgelegten und nachfolgend aufgelisteten Aufsätze selbstständig und nur mit den Hilfen angefertigt habe, die im jeweiligen Aufsatz angegeben oder zusätzlich in der nachfolgenden Liste aufgeführt sind. In der Zusammenarbeit mit den angeführten Koautoren war ich mindestens anteilig beteiligt. Bei den von mir durchgeführten und in den Aufsätzen erwähnten Untersuchungen habe ich die Grundsätze guter wissenschaftlicher Praxis, wie sie in der Satzung der Justus-Liebig-Universität Gießen zur Sicherung guter wissenschaftlicher Praxis niedergelegt sind, eingehalten.

- Schuhmacher, M.C., Philippi, S., 2021. Devils in Disguise? The Impact of Equity Investors on Start-ups' Survival Chances. Working Paper.
- Philippi, S., Masiak, C., Schuhmacher, M. C., Block, J. H., 2021. The Regional Context in Venture Capital Investments: A Longitudinal Multilevel Study of High-tech Start-ups. Working Paper.
- Philippi, S., Schuhmacher, M.C., Bastian, N., 2021. Attracting Investors in Initial Coin Offerings: The Relevance of Specific Technological Capabilities for Fundraising Success. Review of Corporate Finance 1 (3-4), 455-485, http://dx.doi.org/10.1561/114.00000010.

Gießen, 06.05.2021

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Stephan Philippi