Essays on new and established types of entrepreneurial finance: venture capital, business angels, and the emergence of initial coin offerings (ICOs)

Habilitationsschrift

(postdoctoral thesis)

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List of abbreviations

BA	Business angel
BHR	Buy-and-hold returns
BTBF	Blockchain technology-based firm
DLT	Distributed ledger technology
FO	Family office
GEF	Growth equity fund
ICO	Initial coin offering
LBO	Leveraged buyout fund
NTBF	New technology-based firm
PE	Private equity
RQ	Research question
SEC	United States Securities and Exchange Commission
VC	Venture capital (fund), venture capitalist

Summary

Entrepreneurial ventures are associated with economic growth, job creation, and innovation. Most entrepreneurial ventures need external funding to succeed. However, they often find it difficult to access traditional forms of financing, such as bank loans. To overcome this hurdle and to provide entrepreneurial ventures with badly-needed external capital, many types of entrepreneurial finance have emerged over the past decades and continue to emerge today. Inspired by these dynamics, this postdoctoral thesis contains five empirical studies that address novel questions regarding established (e.g., venture capital, business angels) and new types of entrepreneurial finance (i.e., initial coin offerings).

Focusing on established types of entrepreneurial finance, Chapter 2 assesses how private equity investors conduct investment decisions. Chapter 2 uses an experimental conjoint analysis to investigate and compare the investment criteria of 749 investors and distinguishes between family offices, business angels, venture capital funds, growth equity funds, and leveraged buyout funds. In addition to identifying the most important investment criteria (i.e., revenue growth, value-added of product/service, the management team's track record), Chapter 2 reveals considerable differences across investor types regarding the importance attached to these investment criteria.

Chapter 3 focusses on business angels' decision to syndicate investments. Specifically, Chapter 3 argues that the personality of business angels influences syndication behavior and uses a novel method of language analysis based on business angels' Twitter statements to infer their personality. Analyzing data from 3,234 syndication decisions of 1,348 business angels, the results show that some personality traits indeed influence the likelihood of syndication.

Chapter 4 introduces initial coin offerings (ICOs) as a new type of entrepreneurial finance. ICOs are particularly suitable for funding highly innovative ventures in the blockchain sector and represent one of the most recent developments in entrepreneurial finance. Chapter 4 presents an initial study

that empirically examines the determinants of funding raised in 423 ICOs. Building on signaling theory, Chapter 4 highlights the importance of signaling technological capabilities in ICOs. Overall, the results highlight parallels and differences between ICOs and other types of entrepreneurial finance.

Chapter 5 assesses ICO investors, thereby extending Chapter 4's findings to provide a comprehensive account of ICOs. Drawing on data obtained from a survey of 517 ICO investors, Chapter 4 first identifies ICO investors' motives using exploratory factor analysis. The analysis reveals that ICO investors are driven by a set of intrinsic and extrinsic motives, which we categorize as ideological, technological, and financial motives. In addition to assessing each motive's relative importance, Chapter 4 profiles ICO investors across the motives identified.

Finally, Chapter 6 assesses the impact of venture capitalists' participation in ICOs, thereby combining established and new types of entrepreneurial finance. Specifically, Chapter 6 focusses on blockchain technology-based firms' post-ICO performance in terms of growth, liquidity, and profits. Employing econometric methods to control for endogeneity, the results highlight the important role of venture capital in the blockchain sector and suggest that venture capital financing causes firms to perform substantially better than firms without such financing. Further analyses show that venture capital financing also affects other ICO outcomes positively, such as the amount raised.

The results outlined in this postdoctoral thesis provide novel insights for researchers, practitioners, and policymakers interested in entrepreneurial finance. With regard to established types of entrepreneurial finance, Chapters 2 and 3 contribute to a better understanding of investors' decision-making. This includes an identification and comparison of investment criteria across investor types, as well as the introduction of personality as an important determinant for business angels' investment decisions. Chapters 4, 5, and 6 focus on the emergence of ICOs and assess the determinants of ICO success, the motives and profiles of ICO investors, as well as the effects of venture capital financing on post-ICO performance. Since the ICO context is novel and unexplored, the findings of these initial studies contribute to understanding the dynamics of ICOs and their significance for the field of entrepreneurial finance.

Zusammenfassung
(Summary in German)

Startups stehen in Zusammenhang mit Wirtschaftswachstum, Innovationen, und der Schaffung von Arbeitsplätzen. Die meisten Startups benötigen externes Kapital um langfristig erfolgreich sein zu können. Gerade Startups haben jedoch oft Probleme auf traditionelle Finanzierungsformen wie Bankkredite zurückzugreifen. Um dieses Hindernis zu überwinden und Startups mit dringend benötigtem externen Kapital zu versorgen haben sich zahlreiche alternative Formen der Gründungs- und Wachstumsfinanzierung („Entrepreneurial Finance“) herausgebildet. Auch heute kommen ständig neue Finanzierungsformen hinzu. Vor dem Hintergrund dieser Dynamik untersucht die vorliegende Habilitationsschrift in fünf empirischen Studien verschiedene bisher nur wenig betrachtete Fragestellungen rund um etablierte Finanzierungsformen (z. B. Venture Capital und Business Angels) und neue Finanzierungsformen (insbesondere Initial Coin Offerings).

Kapitel 2 legt den Fokus auf etablierte Finanzierungsformen analysiert den Entscheidungsprozess von Private Equity Investoren. Auf der Basis einer experimentellen Conjoint-Analyse mit 749 Investoren vergleicht Kapitel 2 die Investitionskriterien von Family Offices, Business Angels, Venture Capital Fonds, Growth Equity Fonds und Leveraged Buyout Fonds. Neben der Identifikation der wichtigsten Investitionskriterien (z. B. Wertschöpfung von Produkten/Dienstleistungen, Erfolgsbilanz des Managementteams) zeigen die Ergebnisse, dass erhebliche Unterschiede zwischen den Investorengruppen hinsichtlich der Bedeutung bestehen, die diesen Investitionskriterien beigemessen wird.

Kapitel 3 betrachtet die Investitionsentscheidungen von Business Angels und analysiert welche Faktoren erklären ob Business Angels ihre Investitionen syndizieren (d. h. gemeinsam mit anderen Investoren in Startups investieren) oder nicht. Insbesondere argumentiert Kapitel 3, dass die Persönlichkeit von Business Angels deren Syndizierungsverhalten beeinflusst. Kapitel 3 verwendet eine

neuartige Methode der Sprachanalyse um deren Persönlichkeit abzuleiten die auf den Twitter-Nachrichten der Business Angels basiert. Auf Grundlage der Daten von 3.234 Syndizierungsentscheidungen von 1.348 Business Angels zeigen die Ergebnisse, dass einige Persönlichkeitsmerkmale die Wahrscheinlichkeit von Syndizierung tatsächlich beeinflussen.

Kapitel 4 führt Initial Coin Offerings (ICOs) als neue Finanzierungsform ein. ICOs sind insbesondere zur Finanzierung von hochinnovation Startups im Blockchain Bereich geeignet und stellen eine der jünstgen Entwicklungen im Bereich der Wachstums- und Gründungsfinanzierung dar. Kapitel 4 ist eine einführende Studie zum bisher nur wenig untersuchten Thema ICOs. Neben einer ausführlichen Beschreibung von ICOs analysiert Kapitel 4 verschiedene Faktoren die Finanzierungshöhe in ICOs beeinflussen. Auf Basis der etablierten Signaling-Theorie heben die Ergebnisse die Wichtigkeit der technologischen Fähigkeiten von Startups für die Erzielung höherer Finanzierungssummen in ICOs hervor. Die auf Basis einer Analyse von 423 ICOs erzielten Ergebnisse zeigen Gemeinsamkeiten und Unterschiede zwischen ICOs und anderen Formen der unternehmerischen Finanzierung auf.

Kapitel 5 betrachtet Investoren, die sich an ICOs beteiligen und eine weitere entscheidende Partei im ICO-Prozess sind. Aufbauend auf Daten einer Umfrage unter 517 ICO-Investoren identifiziert Kapitel 5 zunächst die Motive der ICO-Investoren anhand einer explorativen Faktoranalyse. Die Analyse zeigt, dass ICO-Investoren von einer Reihe von intrinsischen und extrinsischen Motiven angetrieben werden, die sich als ideologische, technologische und finanzielle Motive klassifizieren lassen. Zusätzlich zur Bewertung der relativen Bedeutung der einzelnen Motive analysiert Kapitel 5 inwiefern sich ICO-Investoren mit hohen Werten in den jeweiligen Motiven untereinander unterscheiden. Mit diesen Ergebnissen erweitert Kapitel 5 die die in Kapitel 4 erzielten Ergebnisse und ermöglicht so eine ganzheitliche Einordnung von ICOs.

Schließlich untersucht Kapitel 6 die Auswirkungen der Beteiligung von Venture Capital-Investoren an ICOs und kombiniert so etablierte und neue Formen der Gründungsfinanzierung. Insbesondere konzentriert sich Kapitel 6 auf die Performance (Wachstum, Liquidität und Gewinn) von Startups in Folge eines ICOs. Durch den Einsatz ökonometrischer Methoden zur Kontrolle von Endogenität heben die Ergebnisse die wichtige Rolle von Venture Capital im Blockchain Bereich hervor. Insbesondere deuten die Ergebnisse darauf hin, dass Venture Capital-Finanzierungen dazu führen, dass Unternehmen eine wesentlich bessere Performance erzielen als Unternehmen ohne eine solche Finanzierung. Weitere Analysen zeigen, dass sich eine Venture Capital-Finanzierung auch auf andere ICO-Ergebnisse positiv auswirkt, wie zum Beispiel die Höhe der eingesammelten Finanzierung.

Die in dieser Habilitationsschrift skizzierten Ergebnisse liefern neue Erkenntnisse für am Bereich der Gründungs- und Wachstumsfinanzierung interessierte Forscher, Praktiker und politische

Entscheidungsträger. Im Hinblick auf etablierte Finanzierungsformen tragen Kapitel 2 und 3 zu einem besseren Verständnis der Entscheidungsfindung von Investoren bei. Dazu gehören die Identifizierung und der Vergleich von Investitionskriterien über Investorengruppen hinweg sowie die Einführung von Persönlichkeit als wichtiger Determinante für die Investitionsentscheidungen von Business Angels. Kapitel 4, 5 und 6 konzentrieren sich auf die Entstehung von ICOs und bewerten die Determinanten des ICO-Erfolgs, die Motive und Profile von ICO-Investoren sowie die Auswirkungen der Venture Capital-Finanzierung auf die Performance nach dem ICO. Da der ICO-Kontext neu und unerforscht ist, tragen die Ergebnisse dieser Studien dazu bei, die Dynamik von ICOs und deren Bedeutung für den Bereich der der Gründungs- und Wachstumsfinanzierung zu verstehen.

Chapter 1

Introduction

The introductory chapter of this postdoctoral thesis ("Habilitationsschrift") proceeds as follows: Section 1.1 briefly outlines the motivation and research context of this thesis. Section 1.2 describes the chapters in more detail and outlines each chapter's main research question. Finally, Section 1.3 provides an overview of the chapters' publication status.

1.1 Motivation and research context

Entrepreneurship plays a crucial role in most societies because it is associated with economic growth, the creation of jobs, and innovation (Block et al., 2017). As such, the field of entrepreneurship is of high interest to practitioners, researchers, and policymakers.

Today, many countries try to stimulate entrepreneurship and foster the benefits of a thriving entrepreneurship ecosystem. These policies frequently target the area of entrepreneurial finance, which refers to the funding of entrepreneurial ventures. For example, the German Federal Ministry for Economic Affairs and Energy (Bundesministerium für Wirtschaft und Energie, BMWi) currently offers governmental accelerator programs, venture capital, and grants to entrepreneurial ventures seeking finance. Additionally, the BMWi provides financial incentives to investors willing to provide capital to entrepreneurial ventures (BMWi, 2019).

The acquisition of external finance is a crucial hurdle that entrepreneurial ventures need to overcome to succeed (e.g., Carpenter and Peterson, 2002). However, these ventures often find it difficult to access traditional forms financing (e.g., bank financing), since they are surrounded by a high degree of uncertainty. This is, for example, because entrepreneurial ventures often lack resources (e.g., collaterals, internal cash-flows, employees, assets) (Block et al., 2018a) and because a considerable information asymmetry exists between ventures and investors (Gompers and Lerner, 2001). This uncertainty is particularly high for ventures that develop or build on new technologies (Baum and Silverman, 2004).

Against this background, several entities have emerged that provide entrepreneurial ventures with much-needed capital. Most prominently, venture capital (VC) is a financial intermediary that specializes in the financing of highly innovative entrepreneurial ventures in the presence of high uncertainty (e.g., Gompers and Lerner, 2001; Puri and Zarutskie, 2012). Among the types of entrepreneurial finance, VC has received the most attention from theory and practice due to its importance for funding new ventures. Also, the contribution of VC to innovation and economic growth is well documented (e.g., Kortum and Lerner, 2001; Samila and Sorenson, 2001). Other more established providers of entrepreneurial finance include business angels (BAs). BAs are individuals that invest their own money in entrepreneurial ventures and are particularly important in very early funding stages (Hellmann and Thiele, 2015). Other providers of entrepreneurial finance that are primarily active in later stages include growth equity funds (GEFs) (Gompers et al., 2016a) or leveraged buyout funds (LBOs) (Kaplan and Stromberg, 2009).

The entrepreneurial finance landscape is highly dynamic. New types of funding continuously emerge in addition to these more traditional forms of entrepreneurial finance (for an overview, see Block et al., 2018a). For example, technology-related factors often lead to the development of novel types of entrepreneurial finance. The emergence of crowdfunding is a recent and major development, both from a practical as well as from a theoretical point of view. Crowdfunding allows entrepreneurial ventures to collect funding from a large crowd of individual (and often private) investors via an open call on the internet (Belleflamme et al., 2014; Mollick, 2014). Here, the internet has enabled the emergence and surge in crowdfunding, which has vast potentials to democratize entrepreneurial finance (e.g., Mollick and Robb, 2016). Most recently, initial coin offerings (ICOs) have emerged as a new form of entrepreneurial finance that is discussed vividly by practitioners, researchers, and policymakers. ICOs leverage blockchain technology to collect financing without intermediaries. Since the first ICO was conducted in July 2013, thousands of ICOs have followed with funding volumes surpassing those realized in crowdfunding (e.g., Fisch, 2019; Lyandres et al., 2018).

Inspired by these dynamics, research in entrepreneurial finance is continuously evolving, and there are plenty of novel avenues to explore. In this postdoctoral thesis, I address novel questions about established and new types of entrepreneurial finance.

1.2 Chapters and research questions

This thesis contains five empirical studies. Two of these studies (Chapters 2 and 3) concern traditional providers of entrepreneurial finance. Specifically, Chapter 2 assesses and compares the decision-making of different types of private equity (PE) investors (e.g., VCs, BAs, GEFs), while Chapter 3 introduces a personality perspective on BA syndication based on BA's digital footprints in Twitter. The remaining studies focus on the emergence of ICOs. While Chapter 4 introduces the concept of ICOs and explores determinants of ICO success, Chapter 5 assesses ICO investors. Finally, Chapter 6 investigates the role of VC in ICOs, thereby integrating more traditional with novel means of entrepreneurial finance.

1.2.1 Chapter 2: Private equity investment criteria: an experimental conjoint analysis of venture capital, business angels, and family offices

PE investments constitute a crucial asset class and often outperform other investments like public equities (e.g., Ang et al., 2018; Harris et al., 2014; Kaplan and Schoar, 2005). A positive association between PE investments and portfolio firm performance is well documented (e.g., Chemmanur et al., 2011; Kaplan and Stromberg, 2009). The high performance of PE investments is often explained by selection and treatment effects, which refers to PE investor's superior ability to select promising portfolio firms and add value post-investment (e.g., Baum and Silverman, 2004; Chemmanur et al., 2011; Puri and Zarutskie, 2012). Even though most PE investors commit a substantial amount of resources to screening investment opportunities (e.g., Gompers et al., 2016a), little systematic knowledge exists about how PE investors conduct investment decisions. To address this gap, Chapter 2 explores the decision-making process across five different types of PE investors and assesses the following research question (RQ):

RQ 1*: What are PE investors' most important decision criteria and how does the importance attached to these criteria vary across investor types?*

To answer RQ 1, we conduct a large-scale conjoint analysis of 19,474 investment decisions by 749 PE investors. To assess the field of PE investments holistically, we analyze and compare the decision-making of family offices (FOs), business angels (BAs), venture capital funds (VCs), growth equity funds (GEFs), and leveraged buyout funds (LBOs). After assessing the importance attached to seven different investment criteria, we use a multilevel logistic regression model to compare the importance attached to each investment criterion across the different investor types.

1.2.2 Chapter 3: A personality perspective on business angel syndication

BAs play a crucial role in entrepreneurial finance. In addition to providing capital, they provide ventures with other valuable resources such as know-how, expertise, and access to networks (e.g., Dutta and Folta, 2016; Kerr et al., 2014; Prowse, 1998). BAs play a particularly important role in early funding stages (Hellmann and Thiele, 2015). Indeed, various unicorns (e.g., Google and Facebook) famously received their initial round of funding from BAs.

Instead of investing alone, BAs frequently syndicate their investments and invest alongside other investors (e.g., Dimov and Milanov, 2010; Manigart et al., 2006). The decision to syndicate has been explained from multiple perspectives (i.e., financial perspective, networking perspective, resource-based perspective) (e.g., Bygrave, 1987; Dimov and Milanov, 2010; Lockett and Wright, 2001; Manigart et al., 2006). In contrast to other PE investors, BAs are individuals that invest their own money. Since personality shapes a wide set of individual decisions (including investments), BAs' personality might contribute to explaining the individual decision to syndicate. Thus, Chapter 3 assesses the following research question:

RQ 2*: How does personality influence business angels' decision to syndicate?*

Combining research on entrepreneurial finance with personality psychology research, we use the established Big Five personality traits (extraversion, conscientiousness, openness, agreeableness, and neuroticism) and assess their impact on BAs' decision to syndicate. Specifically, we assume that BAs high in extraversion, agreeableness, or neuroticism are more likely to engage in syndication, while BAs high in openness and conscientiousness are less likely to engage in syndication. We collect data from 3,234 syndication decisions of 1,348 BAs to assess our hypotheses. To capture BAs' personality, we draw on a novel method of personality assessment that infers BAs' personality from their Twitter activity.

1.2.3 Chapter 4: Initial coin offerings (ICOs) to finance new ventures

ICOs are a novel type of entrepreneurial finance that is particularly suitable for funding highly innovative ventures in the blockchain sector. ICOs represent one of the most recent developments in entrepreneurial finance. Due to their vast potential, ICOs receive considerable attention from ventures that seek financing, institutional and individual investors that seek investment opportunities, and policymakers that face the task to regulate ICOs. From a research perspective, however, little is known about ICOs and the funding dynamics involved, which can largely be attributed to the recency of the phenomenon. Thus, an initial aspect worthy of investigation concerns the determinants of the success of ICO campaigns. For example, it is unclear whether these determinants resemble factors identified in related fields of entrepreneurial finance, such as crowdfunding or VC, or whether ICOs underlie different dynamics (e.g., Ahlers et al., 2015; Baum and Silverman, 2004; Mollick, 2014). In addition to introducing ICOs to entrepreneurial finance research, Chapter 4 thus investigates the following research question:

RQ 3*: What factors determine the amount of funding raised in ICOs?*

Chapter 4 first proposes a definition of ICOs. Then, Chapter 4 describes the funding process of ICOs in detail and gives a market overview of ICOs to allow a better classification of the phenomenons' economic significance. To explore the determinants of the amount raised in ICOs, I then draw on signaling theory (Spence, 1973). Specifically, I argue that high-quality ventures will try to signal higher technological capabilities to investors since technological capabilities are an essential prerequisite for success in the ICO context. To test the assumptions empirically, I collect a sample of 423 ICOs from various data sources. Using multivariate regression analysis, I then explore determinants of the funding raised, emphasizing indicators of ventures' technological capabilities.

1.2.4 Chapter 5: Motives and profiles of ICO investors

The nascent ICO research mainly investigates ICOs from the ICO-conducting ventures' perspectives (e.g., Chapter 4; Ante et al., 2018; Momtaz, 2019a). In contrast, little is known about investors that provide funding in ICOs and thus constitute another crucial party involved in the ICO process. So far, researchers and practitioners mostly rely on anecdotal evidence on the profiles and motives of ICO investors. For example, a widely held assumption is that investors are mainly attracted by the potentially high returns in ICOs (e.g., Adkisson, 2018; Cohney et al., 2018; Madeira, 2018). However, crowdfunding research shows that investors in internet-based forms of microfinance are often motivated by a diverse set of motives. While extrinsic (i.e., financial) motives are important, intrinsic motives, such as being part of a community or supporting a cause, also drive investment behavior (e.g., Allison et al., 2015; Geber and Hui, 2013; Pierrakis, 2019). Chapter 5, therefore, assesses the following multi-faceted research question:

RQ 4*: What are ICO investors' motives to invest in ICOs, what is their relative importance, and how can ICO investors be profiled based on their motives?*

ICO investments are generally pseudonymous, which means that the investor usually does not have to reveal his identity when investing in ICOs. Therefore, we surveyed 517 ICO investors in mid-2018. Building on self-determination theory (Deci and Ryan, 1985) and research on investment motives in crowdfunding, we then conduct an exploratory factor analysis to identify ICO investment motives and their relative importance. Building on the identified motives, we employ regression analysis to profile ICO investors and identify correlates between high scores in the motives and other characteristics.

1.2.5 Chapter 6: Venture capital and the performance of blockchain technology-based firms: evidence from ICOs

VCs preferably invest in high-growth markets and new technologies (e.g., Rosenbusch et al., 2013; Zacharakis et al., 2007). Both aspects apply to the blockchain sector. The sector shows remarkable growth (Lyandres et al., 2018) and blockchain technology constitutes a revolutionary technological innovation with vast potentials (e.g., Elnaj, 2018; Swan, 2015). Hence, blockchain-technology based firms (BTBFs) should constitute attractive targets to VCs seeking investment opportunities.

Indeed, VCs seem to increasingly engage in new forms of digital finance, such as ICOs (e.g., Huang et al., 2019; Kastelein, 2017; Kharif and Russo, 2018). In spite of this initial evidence, little systematic knowledge exists on the role of VCs in the financing of BTBFs and their participation in ICOs in particular. However, understanding whether and how established institutional investors engage in ICOs is crucial for both theory and practice. Thus, Chapter 6 investigate the following research question:

RQ 5*: How does VC financing influence BTBFs' post-ICO performance?*

To address this question, we construct a comprehensive dataset of ICOs, their post-ICO performance, and VC participation. Our main analyses comprise 565 BTBFs (out of which 189 received VC financing). To disentangle selection (i.e., VCs select with superior ventures) and treatment effects (i.e., VC involvement leads to superior performance), we employ a restricted control function approach (Bertoni et al., 2011; Colombo and Grilli, 2010). We also utilize a range of performance measures (e.g., growth, liquidity, buy-and-hold returns) and assess venture's long term performance. Finally, we assess the relationship between VC participation and measures of ICO success, such as funding amount and ICO duration.

1.2.6 Chapter 7: Conclusion

The final chapter concludes this postdoctoral thesis by briefly summarizing the main findings of each chapter. Also, Chapter 7 recapitulates the findings' main implications for theory and practice and ends with a description of avenues for further research.

1.3 Chapters' publication status

Four of the studies (Chapters 2, 3, 4, and 5) are published in leading peer-reviewed journals (*Journal of Banking & Finance*, *Journal of Business Research*, *Journal of Business Venturing*, *Journal of Corporate Finance*). One chapter (Chapter 6) is currently submitted to a journal and is under review. Table 1.1 provides an overview of the publication status of the chapters included in this thesis.

Table 1.1: Publication status of the chapters included in this postdoctoral thesis'

Chapter	Full title	Publication status	Co-authors	Reference
2	Private equity investment criteria: an experimental conjoint analysis of venture capital, business angels, and family offices	Published in *Journal of Corporate Finance*	Block, J., Vismara, S., Andres, R.	Block et al. (2019b)
3	A personality perspective on business angel syndication	Published in *Journal of Banking & Finance*	Block, J., Obschonka, M., Sandner, P.	Block et al. (2019a)
4	Initial coin offerings (ICOs) to finance new ventures	Published in *Journal of Business Venturing*	-	Fisch (2019)
5	Motives and profiles of ICO investors	Published in *Journal of Business Research*	Masiak, C., Vismara, S., Block, J.	Fisch et al. (2019)
6	Venture capital and the performance of blockchain technology-based firms: evidence from ICOs	Submitted	Momtaz, P.	Fisch and Momtaz (2019)

Chapter 2

Private equity investment criteria: an experimental conjoint analysis of venture capital, business angels, and family offices

We use an experimental conjoint analysis to investigate the investment criteria of 749 private equity investors, distinguishing between family offices, business angels, venture capital funds, growth equity funds, and leveraged buyout funds. Our results indicate that revenue growth is the most important investment criterion, followed by the value-added of the venture's product/service, the management team's track record, and profitability. Regarding differences across investor types, we find that family offices, growth equity funds, and leveraged buyout funds place a higher value on profitability as compared to business angels and venture capital funds. Venture capital funds, in turn, pay more attention to companies' revenue growth, business models, and current investors. With these results, our study contributes to the corporate finance literature by deepening our understanding of how different types of private equity investors make investment decisions.

This chapter is based on

Block, J., Fisch, C., Vismara, S., Andres, R., 2019. Private equity investment criteria: An experimental conjoint analysis of venture capital, business angels, and family offices. *Journal of Corporate Finance*, 58(10), 329–352.

2.1 Introduction

Prior research in corporate and entrepreneurial finance has comprehensively investigated the effects of private equity (PE) financing. PE investments are associated with improvements in operating performance (Kaplan and Stromberg, 2009) and oftentimes outperform investments in public equity markets (e.g., Ang et al., 2018; Braun et al., 2017; Harris et al., 2014; Kaplan and Schoar, 2005; Phalippou and Gottschalg, 2009; Robinson and Sensoy, 2013). These findings are consistent across different types of PE investments, ranging from leveraged buyout investments (e.g., Kaplan, 1989) to venture capital investments (e.g., Chemmanur et al., 2011).

The increased performance of PE investments can be ascribed to both selection and treatment effects (Bengtsson and Sensoy, 2011; Bernstein et al., 2016; Chemmanur et al., 2011; Rin et al., 2013; Puri and Zarutskie, 2012). In contrast to stock markets or debtholders, PE investors are active investors who provide their portfolio companies with bundles of value-added activities. The benefits can be direct, through coaching activities or network access, and indirect, through certification effects to third parties (e.g., customers, skilled workers, alliance partners, and financial intermediaries) (e.g., Bottazzi et al., 2008; Gompers and Lerner, 2001; Hellmann and Puri, 2002; Korteweg and Sorensen, 2017; Lerner, 1995). The skills of PE investors, however, do not only lie in nurturing portfolio companies. As recently documented in a survey by Gompers et al. (2016a), PE investors place a heavy emphasis on both their ability to select promising companies as well as their capacity to add value through financial and operational engineering.

Despite the importance of the investment selection, however, only a few studies have yet assessed how PE investors actually select their investments and conduct investment decisions.[1] This is lamentable, considering that PE investors devote considerable resources to evaluating and screening investment opportunities (Kaplan and Stromberg, 2001; Gompers et al., 2016a). Their investment process starts with screening many businesses, although they ultimately only invest in a few companies. Gompers et al. (2016a), for instance, report that for every hundred opportunities considered, the average PE investor deeply investigates 15, signs an agreement with about eight, and closes fewer than four.

Although the decision making of PE investors is often debated (e.g., Gompers and Lerner, 2001; Kaplan and Stromberg, 2004), this study is among the first to assess the investment criteria of PE investors. Empirical evidence on their investment criteria is indeed scarce, arguably due to the empirical challenges of isolating the effects of different company characteristics. This is not possible using observational data, as it would require assessing investors' preferences between two identical

[1] Since PE deals involve at least two parties, selection effects pertain to both the PE investors' and the entrepreneurs' sides of the market. Although the source of deal flow (and the related matching process) is a relevant aspect in the analysis of PE (Schwienbacher, 2007, 2013; Sorensen, 2007), we focus on PE investment criteria in this study. However, we acknowledge that these criteria might be influenced by entrepreneurial choices among different funding sources.

companies that only differ in predetermined characteristics. The experiment by Bernstein et al. (2017) uses correspondence testing methodology to randomize investors' information sets about company characteristics in nearly 17,000 e-mails. They vary the characteristics revealed in e-mails and record when investors click and choose to learn more about the particular company. Similarly, in our study, we randomly vary investors' information sets in a tightly controlled information environment.

We compare decision-making across different investor types using a large-scale conjoint analysis of 19,474 screening decisions by 749 PE investors, which we obtained by contacting 15,600 investment professionals listed in Pitchbook. Conjoint analysis enables a more accurate representation of the actual decision behavior and the underlying preference structure of participants, relative to post hoc approaches such as questionnaires and interviews (e.g., Shepherd and Zacharakis, 1999). Usually, PE investors assess companies holistically and evaluate multiple criteria simultaneously. In conjoint analysis, decision criteria are measured conjointly. For example, investment decisions involve making trade-offs between criteria, which can be captured with conjoint analysis. This experimental method requires participants to make a series of assessments based on a discrete set of company attributes. Specifically, the attributes used in our study are (1) profitability, (2) revenue growth, (3) track record of the management team, (4) reputation of current investors, (5) business model, (6) value-added of product/service, and (7) international scalability. Every participant in the experiment needed to evaluate multiple companies that differ only in the specifications of the above attributes (e.g., 20% revenue growth for company 1 versus 50% revenue growth for company 2) and decide in which company they would invest. Then, a multilevel logistic regression model evaluates and compares the importance of the different investment criteria.

The conjoint experiment enables a better understanding of the investment criteria of investors and allows a comparison of these criteria across investor types. In fact, considerable differences in the decision-making of different investor types likely exist (Lerner et al., 2007). While there is an established literature on the characteristics and behavior of specific types of investors, a broader perspective is underdeveloped so far (Hellmann et al., 2013). A more fine-grained analysis is needed, as the supply side of entrepreneurial finance ecosystems comprises a very diverse set of investor types. Since we aim to study decision-making comprehensively, we distinguish the following investor types: (1) *Family offices (FOs)* are organizations that manage the wealth of business families by taking actions (i.e., investments) to sustain and grow their wealth (Gilding, 2005; Gray, 2005). Prominent examples of FOs include Horizons Ventures, the Hong-Kong-based FO of the Kashing family, and Madrone Capital Partners, the US-based FO of the Walton family (Walmart). Despite their economic relevance and long history, accessing information about FOs is difficult for both researchers and market participants because FOs do not have to disclose information about their investments. Quantitative information on FOs is scarce, making them a particularly attractive investor type for our experiment-based research. (2) *Business angels (BAs)* are wealthy individuals that invest their own money. As such, they are an important pillar of entrepreneurial finance and have become an important source of funding in recent years (Kerr et al., 2014; Hellmann and Thiele, 2015). (3) *Venture capital funds (VCs)* are the best-researched investor type in entrepreneurial finance. Here, VCs serve as an important benchmark to be able to understand and classify differences between VCs and other investor types. (4) *Growth equity funds (GEFs)* constitute an investor type that is particularly crucial in later-stage financing (Gompers et al., 2016a; Ritter, 2015). (5) *Leveraged buyout funds (LBOs)* constitute our final investor type (e.g., Cumming et al., 2007). In a leveraged buyout, a company is acquired by an investment firm using a relatively small portion of equity and a relatively large portion of outside debt financing (Kaplan and Stromberg, 2009).

We make the following contributions. First, we identify the relative importance of PE investors' investment criteria. Overall, the most important investment criteria are (1) revenue growth, (2) value-added of product/service, and (3) management team track record. International scalability, current profitability, business model, and the reputation of existing investors are relevant but of lower importance. The main aspect investigated by previous studies is, arguably, the importance placed on the management team (the "jockey", in Kaplan et al., 2009) relative to the business model (the "horse"). Although the team has been recognized as important in some studies about VC preferences (e.g., Kaplan and Stromberg, 2004), Kaplan et al. (2009) argue that, in theory, VCs should place more weight on business models since companies' business lines remain stable while management turnover is substantial. Recently, Gompers et al. (2019) report that 95% of the VCs in their survey mention the management team as an important factor, 47% as the most important factor. Similarly, the experiment by Bernstein et al. (2017) reveals that BAs are highly responsive to information about the founding team, whereas information about traction and current investors does not lead to significantly increased interest. Adding to this discussion, we find that the management team is an important investment criterion for our participants. However, we also find that investors rate revenue growth and the value-added provided by the company's product or service to be more important than the management team's track record.

Second, we contribute to prior research by comparing the importance of the respective investment criteria across different investor types. While previous literature has suggested that considerable differences in the decision-making of different investor types likely exist (Lerner et al., 2007), a systematic empirical assessment of these differences is absent. Further adding to this literature, we incorporate FOs as an investor type that prior corporate finance research has largely neglected. Our study sheds light on the investment criteria of FOs and finds that, relative to other PE investors, FOs attribute greater importance to the profitability of portfolio companies but less importance to revenue growth. An explanation is that by undertaking risky decisions, the managers of FOs risk losing family wealth and jeopardize the financial and social well-being of future family generations. They are therefore more concerned with the conservation of irreplaceable capital through investments in already profitable companies, rather than bearing the risk and potentially high returns of high-growth companies.

2.2 Research design

2.2.1 Data and sample

We identified investors and investment professionals in Pitchbook, which is one of the most comprehensive databases in entrepreneurial finance and is regularly used for research in the field of PE investments (e.g., Kaplan and Lerner, 2016; Paglia and Harjoto, 2014). The information provided in Pitchbook is mainly based on disclosed information from limited partners, filings of national regulators, and other public information. The advantage of Pitchbook relative to alternative data sources is that it reports information on investors' teams as well as their (individual) contact details, in addition to information on the investment entity (Brown et al., 2015). We use this information to create our sample of investors and investment professionals, which we identified in 2016.

We first filtered Pitchbook by investor type (i.e., funds), selecting all investment entities classified as a VC, FO, buyout fund, or GEF, including multiple investor types. Second, we only considered investors that had done at least one equity deal in the last ten years (as of 2016) that was classified as series A, B, C, D (or later), or expansion. This was done to ensure that participants in the experiment actually had some experience with regard to PE investments. Third, we identified every investment professional in Pitchbook working for these investment entities and removed those who had missing values with regard to e-mail and location.

This approach led to the identification of 15,600 investment professionals which we invited via e-mail to participate in our research. We sent a total of three reminders over five months and collected 749 responses (response rate = 6.2%) in total. We asked participants about the type of investor they work for as Pitchbook's classification can contain multiple classifications per investor. For example, an investor could be classified as a VC and FO simultaneously. Out of the 749 respondents, 59 (7.9%) worked for FOs, 20 (2.7%) for/as BAs, 396 (52.9%) for VCs, 189 (25.2%) for GEFs, and 85 (11.3%) for LBOs. In line with previous studies (e.g., Graham and Harvey, 2001), the experiment was run as an anonymous survey as data collected about investment behavior is sensitive and anonymity is required to fully comply with the latest data security legislation (EU-GDPR/18 General Data Protection Regulation).

Table 2.1: Sample selection and representativeness

This table compares the composition of the population of 15,600 investors in Pitchbook with our sample of 749 participants that took part in our experiment. The initial population was first filtered from Pitchbook by investor type (i.e., funds). Investors needed to be classified as a venture capital fund, corporate venture capital fund, family office, buyout fund, or growth equity fund. Second, we considered only investors that had done at least one equity deal in the last ten years (as of 2016) that was classified as series A, B, C, D (or later), or expansion. Third, we identified every individual investor (= person) listed in Pitchbook working for these investors and removed those individuals who had missing values with regard to e-mail and location. This approach led to the identification of 15,600 individual investors which we invited via e-mail to participate in our research. We sent a total of three reminders letters over five months. In total, we collected 749 responses (response rate = 6.2%). We asked participants about the type of investor they work for (self-selection) as Pitchbook's classifications can contain multiple classifications per investor. For example, an investor could be classified as a VC and FO simultaneously.

Panel A: Pitchbook population

Investor type	*N*	*(%)*
Venture capital fund	8,149	(52.2%)
Private equity companies	3,214	(20.6%)
Family office	503	(3.2%)
Multiple investor types	3,734	(23.9%)
Total	*15,600*	*(100%)*

Panel B: Sample of participants

Investor type	*N*	*(%)*
Venture capital fund	396	(52.9%)
Growth equity fund	189	(25.2%)
Leveraged buyout fund	85	(11.3%)
Family office	59	(7.9%)
Business angel	20	(2.7%)
Total	*749*	*(100%)*

To assess the representativeness of our sample, we first compare the participants in our experiment to the population of investors retrieved from Pitchbook. Overall, the representation of each investor type in our experiment is similar to the distribution of investor types in the full sample, as illustrated in Table 2.1.[2] Second, we test for non-response bias by comparing participants to non-participants (e.g., Armstrong and Overton, 1977). The results are displayed in Table 2.2, which reports the mean values of the population retrieved from Pitchbook (N = 15,600), our final sample (N = 749), and a test for differences between these mean values. The differences are not statistically significant in most cases. For example, most of our participants (87.8%) are male with a slightly higher percentage relative to the percentage of males in the initial Pitchbook population (85.8%). Minor differences exist with regard to the respondents' position in the company. In the initial population, 49.3% were partners or CEOs (51.8% in the final sample), 22.8% (19.6%) were directors or principals, 14.9% (16.5%) were investment managers, and 12.4% (12.0%) worked as analysts.

Table 2.2 also reports investors' geographical distribution, with a general consistency between the initial Pitchbook population and the sample of participants. While 57.1% of the individuals in the population are located in Europe, 60.7% of the final participants are European. The percentage of African investment professionals is significantly higher in our sample as compared to the population.

[2] The fractions obtained from Pitchbook are slightly biased downwards because 23.9% of the investors are coded as "multiple investor types". In our survey, these individuals assigned themselves to the type that fit best. For example, the full population in Pitchbook contained 52.2% VCs, while our sample includes 52.9% VC.

However, they constitute still a small proportion of the final sample (0.9%). We, therefore, conclude that a non-response bias should not influence our results in a major way.

Table 2.2: Assessment of a non-response bias

To assess whether a non-response bias potentially influences our results, we compare our initial sample (N = 15,600) to our final sample (N = 749) along with several characteristics that were recorded in Pitchbook. The first column reports the mean values in the initial population. The second column reports the mean values of our final sample. The final column reports the difference between the mean values along with a significance test. Significant values indicate statistically significant differences. * < 0.10, ** p < 0.05, *** p < 0.01.

Variable	(1) Initial population (N = 15,600)	(2) Final sample (N = 749)	(1) vs. (2)
Gender			
Male	0.858	0.878	0.020
Position in company			
Partner or CEO	0.493	0.518	0.025
Director or principal	0.228	0.196	-0.032*
Investment manager	0.149	0.165	0.016
Analyst	0.124	0.120	-0.004
Location of investment company			
Europe	0.571	0.607	0.036*
Asia	0.079	0.098	0.019*
Africa	0.004	0.009	0.005***
North America	0.280	0.246	-0.034*
South America	0.033	0.020	-0.013*
Oceania	0.031	0.018	-0.013*

We assess a potential late-response bias, which is present if early participants in the experiment significantly differ from late participants (Graham and Harvey, 2001). To assess this bias, we split the final sample into early participants (first half of the respondents, N = 375) and late participants (second half of the respondents, N = 374) and compare their mean values with regard to individual characteristics using a t-test. The results are reported in Table 2.3. For example, the results show that 85.5% of the early participants were male, while 90.3% of the late participants were male. This indicates that females were slightly under-represented among late respondents. Also, early participants were slightly more experienced than late respondents. No significant differences exist with regard to the variables age, tenure, education, entrepreneurial experience, position in the company, or work experience. Thus, the results indicate that no major differences exist between early and late participants.

Table 2.3: Assessment of a late-response bias

To assess whether a late-response bias potentially influences our results, we compare the first half of our participants (N = 375) to the second half of our respondents (N = 374) along with their individual characteristics several characteristics. The first column reports the mean values in the first half of the respondents. The second column reports the mean values of the second half of the participants. The final column reports the difference between the mean values along with the significance of z-tests for proportions. Significant values indicate statistically significant differences. All variables are defined in Table 2.4. * < 0.10, ** p < 0.05, *** p < 0.01.

Variable	(1) First half (N = 375)	(2) Second half (N = 374)	(1) vs. (2)
Gender	0.858	0.903	-0.045*
Age	3.333	3.211	0.122
Experience as investor	11.690	10.470	1.220*
Tenure	7.152	6.796	0.355
Education: law	0.058	0.061	-0.002
Education: business/economics	0.776	0.794	-0.018
Education: natural sciences	0.114	0.098	0.015
Education: engineering	0.250	0.221	0.028
Entrepreneurial experience	0.512	0.502	0.009
Position in the company	1.850	1.925	-0.074
Work experience: startups/SMEs	0.245	0.288	-0.043
Work experience: large companies and startups/SMEs	0.389	0.382	0.006
Work experience: large companies	0.365	0.328	0.036

As in all studies, external validity might be a concern. Fortunately, previous research provides considerable evidence for the external validity of conjoint studies (e.g., Louviere, 1988; Shepherd and Zacharakis, 2018). These studies generally show that the estimated decision behavior in conjoint experiments strongly correlates with real observed behavior. Shepherd and Zacharakis (2018) recommend that conjoint tasks should be representative of the participant’s real tasks in order to ensure external validity. Hence, we conducted a pretest with experienced PE investors, who confirmed that our selection of attributes and attribute levels is an appropriate portrayal of their actual investment decisions.

Among the different types of investors, FOs might be particularly prone to concerns of external validity, as they have received scant attention in previous research. To assess the external validity of our sample of FOs, we refer to the Global Family Office Report (GFOR) (2018), which is one of the most established surveys on FOs to date. The GFOR (2018) provides information based on a sample of 311 FOs. The GFOR (2018) shows that the most prevalent stages in which FOs invest (PE funds and direct investments) are growth stages (72%) and venture stages (57%). These values are similar to our sample, in which 73% of the FOs indicate to invest in growth stages and 66% in early stages. A distinguishing feature is that FOs, compared to the other investor types in our sample, are smaller with regard to assets under management. This is somewhat surprising as reports frequently describe FOs as extremely wealthy investors, whose assets under management revolve around 1,000 $m on average (e.g., Economist, 2018b). The GFOR similarly reports a mean value of 808 $m, while most of the FOs in our sample report assets under management between 100 and 250 $m. However, these reports also acknowledge a large variety across FOs. Unfortunately, the distribution of assets under management is not reported in the GFOR so that it is difficult to conclude whether our sample is biased downwards. With regard to syndication, the GFOR indicates that FOs tend to make co-investments instead of investing alone. Similar, FOs in our sample express a strong preference for syndication. Finally, the GFOR indicates that 38% of the FOs are headquartered in Europe, 34% in North America, 28% in the rest of the world. This indicates that European FOs are overrepresented in our sample, constituting 60% of the participants (25% North America, 15% rest of the world).

2.2.1 Descriptive statistics

Each participant in the experiment filled out a questionnaire with questions on characteristics of the investment entity in which they work, characteristics of the portfolio companies, and individual characteristics. The following subsections provide a descriptive overview of the sample and highlight the particularities of each investor type. First, Table 2.4 defines the variables and descriptive statistics for the full sample. The average investment professional in our sample manages between 100 and 250 $m with a target internal rate of return between 10% and 20%. About one-fourth of the participants invest alone, about one-half invest with one or more other investors, while the remaining one fourth is indifferent to syndication. Most of the participants in the experiment are based in Europe. Coherently, most of the investment companies in which they invest are European. The main industry of their portfolio companies is software and services. The average investment professional is male (88%), between 35 and 45 years old with 11 years of experience as an investor. The educational background of most participants (79%) is business and economics.

Table 2.4: Descriptive statistics and definition of the variables

This table provides an overview of the full sample used in our analysis and displays descriptive statistics along with variable definitions. Panel A describes variables related to characteristics of the investment entity. Panel B describes variables related to characteristics of the portfolio companies. Panel C describes variables related to individual-level variables of the participants. The sample comprises 749 participants.

Panel A: Characteristics of the investment entity

Variable	*Mean*	*S.D.*	*Min.*	*Max.*	*Description*
Assets under management	3.96	1.50	1	6	Investor's assets under management in $m (categorical; 1 = < 10, 2 = 10–25; 3 = 26–100; 4 = 101–250; 5 = 251–1,000, 6 = > 1,000)
Internal rate of return	3.73	0.99	1	6	Investor's internal rate of return in % (categorical; 1 = < 0, 2 = 1–10, 3 = 11–20, 4= 21–30, 5 = 31–40, 6 = > 40)
Cash-on-cash multiple < 1 x	0.21	0.21	0	1	Investor's cash-cash-multiple: percentage of deals that returned invested capital < 1 x
Cash-on-cash multiple 1x–2x	0.27	0.21	0	1	Investor's cash-cash-multiple: percentage of deals that returned invested capital 1x–2x
Cash-on-cash multiple 2x–5x	0.36	0.25	0	1	Investor's cash-cash-multiple: percentage of deals that returned invested capital 2x–5x
Cash-on-cash multiple 5x–10x	0.11	0.13	0	1	Investor's cash-cash-multiple: percentage of deals that returned invested capital 5x–10x
Cash-on-cash multiple > 10 x	0.05	0.08	0	50	Investor's cash-cash-multiple: percentage of deals that returned invested capital > 10 x
Syndication: invest alone	0.24	-	0	1	Syndication: Investor prefers to invest alone (dummy; 1 = yes, 0 = no)
Syndication: with one other investor	0.28	-	0	1	Syndication: Investor prefers to invest together with one other investor (dummy; 1 = yes, 0 = no)
Syndication: with multiple other investors	0.24	-	0	1	Syndication: Investor prefers to invest together with multiple other investors (dummy; 1 = yes, 0 = no)
Syndication: indifferent	0.24	-	0	1	Syndication: Investor is indifferent with regard to syndication (dummy; 1 = yes, 0 = no) (dummy; 1 = yes, 0 = no)
Location: Europe	0.61	-	0	1	Investor's headquarter is located in Europe (dummy; 1 = yes, 0 = no)
Location: North America	0.25	-	0	1	Investor's headquarter is located in North America (dummy; 1 = yes, 0 = no)
Location: Rest of the world	0.14	-	0	1	Investor's headquarter is located in the rest of the world (i.e., not in Europe or North America) (dummy; 1 = yes, 0 = no)
Company size	2.93	0.86	1	4	Number of investment professionals working for the investor (categorical; 1 = 1; 2 = 2–5, 3 = 6–10; 4 = > 10)

Panel B: Characteristics of portfolio companies

Variable	*Mean*	*S.D.*	*Min.*	*Max.*	*Description*
Seed-stage	0.32	-	0	1	Investor invests in portfolio companies in the seed-stage (dummy; 1 = yes, 0 = no)
Early-stage	0.58	-	0	1	Investor invests in portfolio companies in the early-stage (dummy; 1 = yes, 0 = no)
Growth-/expansion-stage	0.62	-	0	1	Investor invests in portfolio companies in the growth-/expansion-stage (dummy; 1 = yes, 0 = no)
Later-stage	0.24	-	0	1	Investor invests in portfolio companies in later stages (dummy; 1 = yes, 0 = no)
Industry: Software and services	0.67	-	0	1	Investor invests in portfolio companies in software and services (dummy; 1 = yes, 0 = no)
Industry: IT infrastructure/systems	0.40	-	0	1	Investor invests in portfolio companies in IT infrastructure/systems (dummy; 1 = yes, 0 = no)
Industry: Financial services	0.34	-	0	1	Investor invests in portfolio companies in financial services (dummy; 1 = yes, 0 = no)
Industry: E-Commerce	0.36	-	0	1	Investor invests in portfolio companies in e-commerce (dummy; 1 = yes, 0 = no)
Industry: Biotechnology and healthcare	0.37	-	0	1	Investor invests in portfolio companies in biotechnology and healthcare (dummy; 1 = yes, 0 = no)
Industry: Media and entertainment	0.28	-	0	1	Investor invests in portfolio companies in media and entertainment (dummy; 1 = yes, 0 = no)
Industry: Consumer products and services	0.42	-	0	1	Investor invests in portfolio companies in consumer products and services (dummy; 1 = yes, 0 = no)
Industry: Industrials and industrial technology	0.40	-	0	1	Investor invests in portfolio companies in industrials and industrial technology (dummy; 1 = yes, 0 = no)
Industry: Energy	0.18	-	0	1	Investor invests in portfolio companies in energy (dummy; 1 = yes, 0 = no)
Industry: Other	0.08	-	0	1	Investor invests in portfolio companies in other industries than above (dummy; 1 = yes, 0 = no)
Location: Europe	0.72	-	0	1	Investor invests in portfolio companies located in Europe (dummy; 1 = yes, 0 = no)
Location: North America	0.43	-	0	1	Investor invests in portfolio companies located in North America (dummy; 1 = yes, 0 = no)
Location: Rest of the world	0.34	-	0	1	Investor invests in portfolio companies located in the rest of the world (i.e., not in Europe or North America) (dummy; 1 = yes, 0 = no)

Table 2.4: Descriptive statistics and definition of the variables (continued)

Panel C: Characteristics of the individual investor

Variable	*Mean*	*S.D.*	*Min.*	*Max.*	*Description*
Gender	0.88	-	0	1	Participant's gender (dummy; 1 = male, 0 = female)
Age	3.27	1.16	1	6	Participant's age (categorical; 1 = less than 25, 2 = 25–34, 3 = 35–44, 4 = 45–54, 5 = 55–64, 6 > 64)
Experience as investor	11.08	8.25	1	48	Participant's years of experience as an investor (number of years)
Tenure	6.99	6.38	1	40	Participant's tenure with their current investor (number of years)
Education: law	0.06	-	0	1	Participant has an educational background in law (dummy; 1 = yes, 0 = no)
Education: business/economics	0.79	-	0	1	Participant has an educational background in business or economics (dummy; 1 = yes, 0 = no)
Education: natural sciences	0.11	-	0	1	Participant has an educational background in natural science (dummy; 1 = yes, 0 = no)
Education: engineering	0.24	-	0	1	Participant has an educational background in engineering (dummy; 1 = yes, 0 = no)
Entrepreneurial experience	0.51	-	0	1	Participant has experience as an entrepreneur (dummy; 1 = yes, 0 = no)
Position in the company	1.89	1.07	1	4	Participant's current position (categorical; 1 = general partner or CxO, 2 = director or principal; 3 = investment manager, 4 = analyst)
Work experience: startups/SMEs	0.27	-	0	1	Individual has work experience mostly in startups/SMEs (dummy; 1 = yes; 0 = no)
Work experience: large companies and startups/SMEs	0.39	-	0	1	Individual has work experience mostly in large companies and startups/SMEs (dummy; 1 = yes; 0 = no)
Work experience: large companies	0.35	-	0	1	Individual has work experience mostly in large companies (dummy; 1 = yes; 0 = no)

Table 2.5: Descriptive statistics across different types of investors

This table outlines differences in the mean values across the different investor types included in our sample. While the first column depicts the mean values of the full sample (N = 749), the following columns refer to family offices (FOs), business angels (BAs), venture capital funds (VCs), growth equity funds (GEFs), and leveraged buyout funds (LBOs). Panel A outlines differences across variables related to characteristics of the investment entity. Panel B outlines differences across variables related to characteristics of the portfolio companies, while panel C outlines differences across variables related to individual-level variables of the participants. The signs in brackets (+/-) indicate whether the respective mean value is significantly larger (+) or smaller (-) than the mean value of the remaining sample. A t-test is used to calculate the significance of each individual mean value. The final column reports the significance level obtained from an analysis of variance (ANOVA), indicating statistically significant differences across groups. All variables are defined in Table 2.2. * < 0.10, ** p < 0.05, *** p < 0.01.

Panel A: Characteristics of the investment entity

Variable	*Full sample (N = 749)*	*FOs (N = 59)*	*BAs (N = 20)*	*VCs (N = 396)*	*GEFs (N = 189)*	*LBFs (N = 85)*	*ANOVA*
Assets under management	3.96	3.54 (-)	1.60 (-)	3.63 (-)	4.54 (+)	5.02 (+)	***
Internal rate of return	3.73	3.68	4.00	3.74	3.73	3.68	
Cash-on-cash multiple < 1 x	0.21	0.22	0.25	0.28 (+)	0.12 (-)	0.08 (-)	***
Cash-on-cash multiple 1x–2x	0.27	0.26	0.26	0.26	0.27	0.33 (+)	
Cash-on-cash multiple 2x–5x	0.36	0.33	0.26	0.28 (-)	0.48 (+)	0.52 (+)	***
Cash-on-cash multiple 5x–10x	0.11	0.13	0.14	0.13 (+)	0.10	0.05 (-)	***
Cash-on-cash multiple > 10 x	0.05	0.06	0.08 (+)	0.06 (+)	0.03 (-)	0.01 (-)	***
Syndication: invest alone	0.24	0.15	0.10	0.07 (-)	0.45 (+)	0.67 (+)	***
Syndication: with one other investor	0.28	0.25	0.25	0.34 (+)	0.20 (-)	0.18 (-)	***
Syndication: with multiple other investors	0.24	0.27	0.45 (+)	0.34 (+)	0.10 (-)	0.06 (-)	***
Syndication: indifferent	0.24	0.32	0.20	0.25	0.25	0.09 (-)	***
Location: Europe	0.60	0.66	0.55	0.60	0.52 (-)	0.76 (+)	***
Location: North American	0.25	0.20	0.20	0.23	0.30 (+)	0.20	
Location: Rest of the world	0.15	0.15	0.25	0.17	0.17	0.04 (-)	**
Company size	2.93	2.42 (-)	1.90 (-)	2.78	3.23 (+)	3.53 (+)	***

Panel B: Characteristics of portfolio companies

Variable	*Full sample (N = 749)*	*FOs (N = 59)*	*BAs (N = 20)*	*VCs (N = 396)*	*GEFs (N = 189)*	*LBFs (N = 85)*	*ANOVA*
Seed-stage	0.32	0.31	0.70 (+)	0.50 (+)	0.04 (-)	0.00 (-)	***
Early-stage	0.58	0.66	0.65	0.85 (+)	0.24 (-)	0.04 (-)	***
Growth-/expansion-stage	0.62	0.73	0.25 (-)	0.47 (-)	0.91 (+)	0.68	***
Later-stage	0.24	0.25	0.00 (-)	0.09 (-)	0.39 (+)	0.71 (+)	***
Industry: Software and services	0.67	0.63	0.70	0.74 (+)	0.60 (-)	0.56 (-)	***
Industry: IT infrastructure/systems	0.40	0.24 (-)	0.35	0.43 (+)	0.36	0.46	***
Industry: Financial services	0.34	0.44	0.15	0.34	0.38	0.25	**
Industry: E-Commerce	0.36	0.34	0.50	0.39 (+)	0.31	0.31	**
Industry: Biotechnology and healthcare	0.37	0.37	0.35	0.38	0.36	0.35	
Industry: Media and entertainment	0.28	0.29	0.25	0.28	0.24	0.32	
Industry: Consumer products and services	0.42	0.53	0.30	0.32 (-)	0.48 (+)	0.71 (+)	***
Industry: Industrials and ind. technology	0.40	0.51	0.20	0.32 (-)	0.42	0.72 (+)	***
Industry: Energy	0.18	0.22	0.10	0.17	0.18	0.21	
Industry: Other	0.08	0.08	0.05	0.07 (-)	0.12 (+)	0.08	
Location: Europe	0.72	0.75	0.55	0.69 (-)	0.69	0.93 (+)	***
Location: North American	0.43	0.49	0.45	0.46	0.43	0.27 (-)	***
Location: Rest of the world	0.34	0.36	0.35	0.37	0.37	0.16 (-)	***

Panel C: Characteristics of the individual investment professional

Variable	*Full sample (N = 749)*	*FOs (N = 59)*	*BAs (N = 20)*	*VCs (N = 396)*	*GEFs (N = 189)*	*LBFs (N = 85)*	*ANOVA*
Gender	0.88	0.90	0.85	0.87	0.90	0.89	
Age	3.27	3.44	3.85 (+)	3.27	3.23	3.16	
Experience as investor	11.08	13.47 (+)	13.05	10.03 (-)	11.59	12.76	***
Tenure	6.99	8.17	6.70	6.75	6.89	7.54 (+)	
Education: law	0.06	0.10	0.00	0.05	0.07	0.06	
Education: business/economics	0.79	0.86	0.75	0.73 (-)	0.85 (+)	0.86	***
Education: natural science	0.11	0.08	0.05	0.15 (+)	0.06 (-)	0.04 (-)	***
Education: engineering	0.24	0.17	0.20	0.29 (+)	0.21	0.11 (-)	***
Entrepreneurial experience	0.51	0.51	0.90 (+)	0.56 (+)	0.41 (-)	0.39 (-)	***
Position in the company	3.11	3.12	3.70 (+)	3.16	2.94 (-)	3.12	**
Work experience: startups/SMEs	0.27	0.39 (+)	0.45	0.31 (+)	0.19 (-)	0.13 (-)	***
Work experience: large companies and startups/SMEs	0.39	0.24 (-)	0.35	0.38	0.47 (+)	0.34	***
Work experience: large companies	0.35	0.37	0.20	0.31 (-)	0.34	0.53 (+)	***

Table 2.5 provides an initial comparison of the investor types. Specifically, Table 2.5 outlines the differences in the mean values across the different investor types included in our sample. While the first column depicts the mean values of the full sample (N = 749), the following columns refer to the respective investor types. The signs in brackets (+/-) indicate whether the respective mean value is significantly larger (+) or smaller (-) than the mean value of the remaining sample. A t-test indicates whether the respective mean value differs from the mean value of the remaining sample. The final column reports the significance levels obtained from an analysis of variance (ANOVA), indicating statistically significant differences across the different investor groups. The results for each investor type are described in detail in the following subsections.

Family offices (FOs)

Our sample includes 59 FOs. Overall, Table 2.5 illustrates that the FOs in our sample do not have many characteristics in which they significantly differ from the other investor types in our sample, making nuanced profiling difficult. For example, the results show that FOs invest in portfolio companies of all stages: 31% of the sampled FOs invest in seed-stage portfolio companies, 66% in early-stage, 73% in growth-/expansion-stage, and 25% in later-stage portfolio companies. Further information on FO's investment portfolios is provided in the GFOR, which outlines that direct equity investments (in developed and developing markets) make up 28% of FO’s portfolio and outlines that 50% of FOs intend to invest more in PE direct investments in the future.

A distinguishing feature is that FOs, compared to the other investor types in our sample, are smaller with regard to assets under management and company size as measured by their number of investment professionals. This is somewhat surprising: While empirical academic research on FOs is virtually non-existent, practice-oriented reports frequently describe FOs as extremely wealthy investors, whose assets under management revolve around 1,000 $m on average (e.g., Economist, 2018b). However, these reports also acknowledge a large variety across FOs.

Another distinguishing characteristic is that FOs’ investment professionals tend to have more experience than those working for other investors, as they have, on average, worked as an investment professional for 13.5 years. Also, investment professionals from FOs have a comparatively high degree of work experience from working in startups or small and medium enterprises (SMEs). However, these investment professionals are not necessarily founders themselves as their own entrepreneurial experience is not significantly different from the remaining sample.

Business angels (BAs)

Our sample comprises 20 BAs, which is the least prevalent group of participants. BAs represent the smallest investor type with regard to assets under management and company size. This is because

BAs are often individual investors that invest their own money and frequently make smaller investments than other investor types (Hellmann and Thiele, 2015; Lerner, 1998). Also, our data reflects that BAs tend to invest in very early-stage companies: 70% of the sampled BAs invest in the seed stage, which is the highest value among all investor types. Simultaneously, BAs are less likely to invest in growth- or later-stage companies when compared with the other investor types (Hellmann and Thiele, 2015). Investing in very early stages involves a comparatively high degree of uncertainty. One way to reduce this uncertainty and to mitigate investment risk is to engage in syndication (Block et al., 2019a [Chapter 3]; Lerner, 1994). Compared to other participants, the sampled BAs have a strong preference to engage in syndication with multiple other investors, which is in line with prior research (e.g., Block et al., 2019a; Manigart et al., 2006). Also, investing in very early stages can lead to potentially large payoffs in a high-risk high-reward fashion. This risky investment strategy corresponds to the fact that BAs report to have achieved a significantly higher share of investments with cash-on-cash multiples larger than factor 10.

With regard to individual characteristics, BAs are older than investment professionals in other investor types and more often have entrepreneurial experience. Again, these findings are in line with previous research which regularly describes BAs as experienced individuals that often possess substantial entrepreneurship experience (e.g., Collewaert and Manigart, 2016). Often, previous entrepreneurial activities are one of the sources of BAs funds.

Venture capital funds (VCs)

VCs represent the largest group of investors in our sample (N = 396). While VCs are larger than FOs and BAs with regard to assets under management and company size, they are significantly smaller than GEFs and LBOs. This is in line with prior research by Gompers et al. (2016a), who point out that GEFs and LBOs are typically larger than VCs. Also, prior research indicates that VCs are very risk-prone, which is reflected in (potentially) large and volatile returns (e.g., Cochrane, 2005). This is reflected in our descriptive statistics: While VCs have a significantly higher share of investments that achieve low cash-on-cash multiples than the other investor types, they also report a significantly higher share of investments with very high cash multiples.

Our descriptive statistics confirm that VCs prefer to invest in early stages and less in later stages than other investor types. For example, 85% of the participants indicated that they invest in early-stage companies, while only 9% indicated that they (also) invest in later-stage companies. However, VCs do not have a preference for seed-stage investments that is as pronounced as for BAs. Like BAs, VCs have a general preference for syndication with one or multiple investors. Again, syndication is frequently used as a strategy to mitigate risk, especially in early-stage investments that contain a high degree of uncertainty (Gompers et al., 2016a).

With regard to individual characteristics of the investment professionals, participants working for VCs had less experience working as investors, less often had a business education, and more often had a background in natural sciences or engineering as compared to the remaining sample. Also, participants working for VCs reported high levels of entrepreneurial experience (second only to BAs) and a high amount of work experience from startups or SMEs instead of large companies.

Growth equity funds (GEFs)

Our sample contains 189 participants from GEFs. With regard to both assets under management and the number of investment professionals, GEFs are significantly larger than FOs, BAs, and VCs. This is in line with prior research by Gompers et al. (2016a) and Ritter (2015), who state that GEFs tend to be larger than most VCs but usually smaller than LBOs. GEFs constitute an investor type that is particularly crucial in later-stage financing (Gompers et al., 2016a; Ritter, 2015). This is reflected in our descriptive statistics, which show that a significantly higher fraction of GEFs invests in later stages as compared to other investors. In particular, 91% stated that they invest in growth-/expansion-stage portfolio companies.

Later-stage investments generally entail a lower investment risk (Gompers et al., 2016a; Ritter, 2015). This is because, at that stage, companies typically have a functioning product and business model and have experienced initial market success. Moreover, company performance measures are more readily available and can be used as investment criteria. The lower investment risk in later-stage deals corresponds to less volatility in investment returns (Cochrane, 2005). In contrast to other PE investors, GEFs achieve a significantly smaller fraction of investments with low cash-on-cash multiples and a significantly higher ratio of cash multiples between 2 and 5 (48% of their investments). Also, since syndication is a means to reduce investment risk, GEFs tend to engage less in syndication and more often invest alone as compared to the other investor types.

GEFs primarily invest in growth- and expansion-stage companies. This specialization is also reflected in individual-level statistics. For example, own entrepreneurial experience of the investment professional may be less important when investing in later-stage companies compared to investing in early-stage ventures. Compared to the early-stage investor types in our sample, individuals working in GEFs indeed have less often own entrepreneurial experience and work experience from working in startups or SMEs versus work experience from large companies. Finally, they more often have a business education, which may be useful when it comes to scaling instead of developing business models.

Leveraged buyout funds (LBOs)

Our sample contains 85 participants from LBOs, which represent the largest investor type in terms of assets under management and the number of investment professionals. This is in line with prior research, which frequently highlights LBOs as an important asset class that is substantially larger than other types of PE investors (Kaplan and Schoar, 2005; Metrick and Yasuda, 2010).

Typically, LBOs invest in mature companies. This is different from investors like VCs and BAs, which typically invest in young or emerging companies (e.g., Kaplan and Stromberg, 2009; Metrick and Yasuda, 2010). Indeed, our descriptive statistics show that the share of seed- and early-stage investments is significantly smaller with LBOs than with other investor types, whereas the fraction of investments in later-stage companies is significantly larger. For investments in mature companies investment uncertainty is lower. Our results reflect this, as LBOs tend to engage in syndication less often than other investors. 67% of LBOs prefer to invest alone. The lower likelihood of syndication may also be related to LBO's large size, which makes syndication less necessary to raise large funding volumes. Cochrane (2005) finds that later-stage deals have less volatility than early-stage deals with regard to returns. This is reflected in LBOs' investment success: With regard to cash-on-cash multiples, LBOs have significantly lower ratios of very low and very high multiples and report significantly more often multiples of average size. 85% of their investments achieve multiples between 1 and 5.

Finally, prior studies acknowledge that LBOs create value through significant managerial improvements (Kaplan and Stromberg, 2009; Rigamonti et al., 2016). However, more mature companies already possess management skills so that LBOs are required to provide a different set of supporting activities than VCs do. Metrick and Yasuda (2010) find that LBO investors build on their prior experience by increasing the size of their funds faster than VCs do. They also describe that LBO investors add value to extremely large companies, whereas VCs can add value primarily to small companies. This has implications for individuals working in LBOs. They have less entrepreneurial experience and have more often gained work experience in larger companies as compared to individuals working for other investor types. This set of experiences makes them well suited to developing large companies.

2.2.3 Experimental design of the conjoint analysis

As the main part of our study, we conduct an experimental conjoint analysis to elicit the decision-making behavior of PE investors. This technique requires participants to make a series of assessments based on a fixed set of attributes. With this approach, decision criteria can be measured conjointly in a multivariate way, allowing a more accurate representation of the actual decision behavior and the underlying preference structure. This approach is frequently used in the context of investor decision-making due to the limitations of post hoc approaches such as questionnaires and interviews (e.g., Shepherd and Zacharakis, 1999). For example, information is collected as the decision is being made, whereas post-hoc methods collect data about a decision after the decision has been made. Therefore, conjoint studies overcome limitations of post hoc approaches, such as a self-reporting or recall bias. Relatedly, conjoint experiments come closer to the investor's actual decision-making scenario. Usually, PE investors assess companies holistically and evaluate multiple criteria simultaneously. This involves making trade-offs between different criteria. These tradeoffs can be captured with conjoint approaches. Recently, Bernstein et al. (2017) used a similar experimental approach to assess the importance of startup characteristics to investors in early-stage companies. In contrast to Bernstein et al. (2017), we are particularly interested in how the importance of investment criteria varies across different investor types.

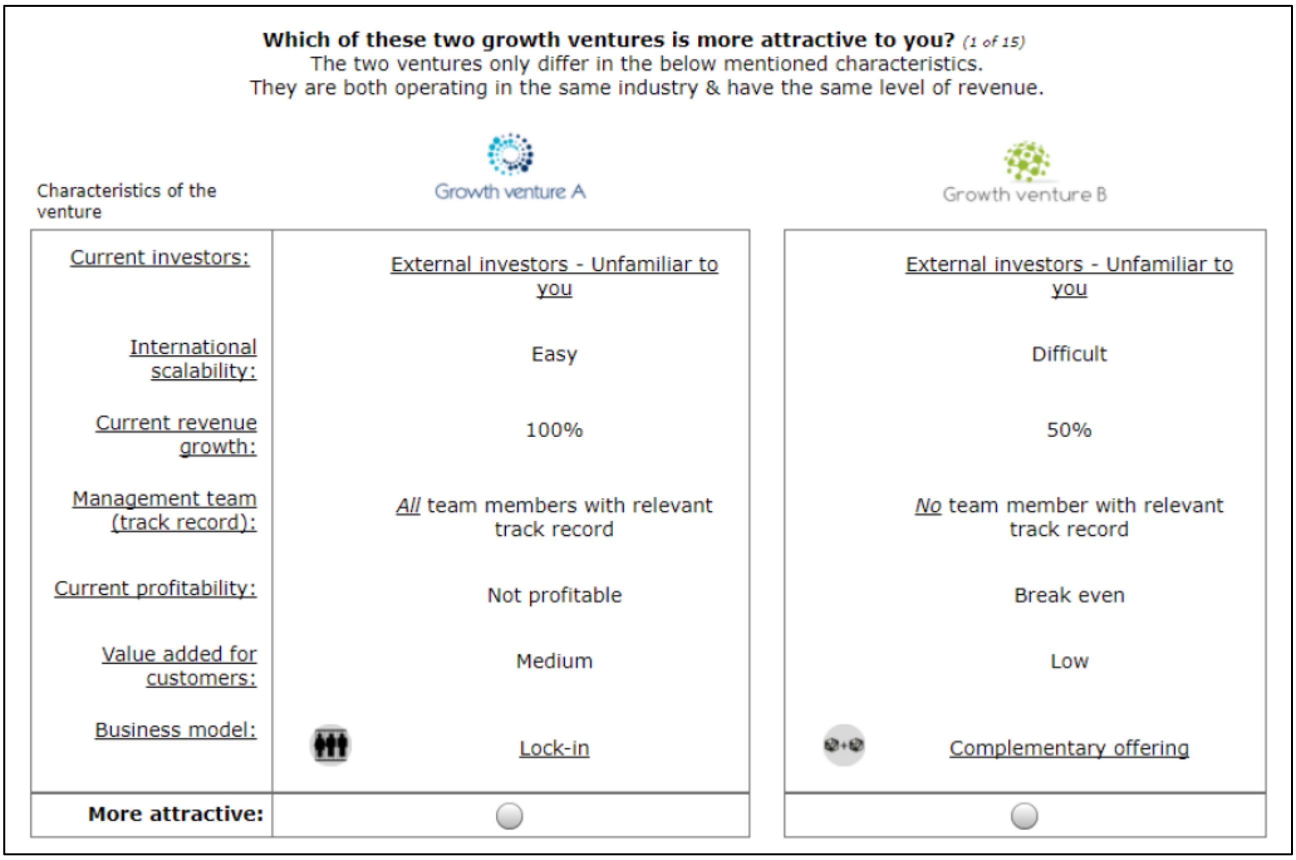
We use a choice-based conjoint analysis (CBC) in which objects (here: companies) that consist of several attributes (here: revenue growth, profitability, reputation of current investors, etc.) are evaluated by participants (here: investment professionals). Participants are asked to make a deterministic investment decision between several hypothetical portfolio companies that differ only in the specifications of the company attributes (e.g., 20% revenue growth for company 1 versus 50% revenue growth for company 2). Before asking the participants to make a series of decisions, they were provided with information on the study and the decision tasks they were going to face. An important advantage of our experimental setting is that we were able to provide respondents with a very detailed description of the (hypothetical) companies they were going to assess. To ensure that the participants in our experiment were thinking about similar (or the same) company when making their investment decision, we included an introductory slide outlining our understanding of the hypothetical companies. They were told that they would be confronted with two different companies that are in a stage of early growth or expansion and we clarified that companies have market traction, a validated business model, multiple paying customers, growth in sales and customers, and multiple employees. To avoid conflicts with the generic screening criteria of investors, the presented companies were said to match the geographical, industrial, and investment size preferences of the participants (Franke et al., 2008).

To identify a list of typical screening criteria used by PE investors, we proceeded in two steps. First, we derived a list of possible criteria from prior research (e.g., Bernstein et al., 2017; Franke et al., 2008; Puri and Zarutskie, 2012). Second, we conducted 19 expert interviews with PE investors from Europe and the US to identify the most relevant criteria used by different investor types. These experts represent several investor types (e.g., VCs, FOs, GEFs). The interviews were transcribed and coded by two researchers to identify the most relevant criteria.[3] Based on this procedure, we derived a list of company attributes and attribute levels. The identified attributes are (1) profitability, (2) revenue growth, (3) track record of the management team, (4) reputation of current investors, (5) business model, (6) value-added of product/service, and (7) international scalability. These attributes or investment criteria are in line with and extend criteria mentioned in previous research, such as Bernstein et al. (2017). Our business model measure is based on the work of Amit and Zott (2001). Table 2.6 provides a detailed description of our operationalization of these criteria as well as their respective levels. In addition to the attributes, Table 2.6 also outlines the respective attribute levels and their descriptions. For example, the attribute "revenue growth" comprises the attribute levels "10% p.a.", "20% p.a.", "50% p.a.", and "100% p.a.". All descriptions outlined in Table 2.6 were also shown to the participants in our conjoint experiment.

Since PE investors assess potential investments holistically, we employ a full-profile CBC, which means that all attributes from Table 2.6 are presented to investors at once. CBC is used in conjunction with a reduced conjoint design (Chrzan and Orme, 2000), as participants would be exposed to too many decision tasks if combinations between all possible variations of attribute levels were presented. Furthermore, the experimental design is asymmetric because the number of attribute levels across attributes is not equal.[4] We created 800 different experimental designs, with each presenting a different sequence of choice tasks with different combinations of attribute levels. Each design consists of the 7 attributes outlined in Table 2.6 whose levels were randomly assigned to two investment opportunities. Each participant was asked to select one of the two alternatives in 15 choice tasks. While 13 of these tasks were randomly assigned, 2 were the same for all participants. These "fixed" tasks were used to determine the test-retest reliability of the participants' choices in the study. Figure 2.1 provides an illustration of a choice task that each participant faced 15 times with varying attribute levels. On average, each choice task took the participants 21 s to complete, which is in line with other research (Johnson and Orme, 1996).

[3] We triangulated the findings from the interviews with archival data and with informal expert interviews.
[4] The experimental design is a balanced-overlapping approach with a fractional asymmetric design, which is a frequently employed design strategy for CBC studies (e.g., Chrzan and Orme, 2000).

Figure 2.1: Exemplary choice task presented to participants



Which of these two growth ventures is more attractive to you? *(1 of 15)*
The two ventures only differ in the below mentioned characteristics.
They are both operating in the same industry & have the same level of revenue.

Characteristics of the venture	Growth venture A	Growth venture B
Current investors:	External investors - Unfamiliar to you	External investors - Unfamiliar to you
International scalability:	Easy	Difficult
Current revenue growth:	100%	50%
Management team (track record):	*All* team members with relevant track record	*No* team member with relevant track record
Current profitability:	Not profitable	Break even
Value added for customers:	Medium	Low
Business model:	Lock-in	Complementary offering
More attractive:	○	○

Notes: In this choice task, every participant was asked to select the company that presents a more attractive investment opportunity for him. Each participant was presented with 15 different choice tasks. While the seven attributes of the companies were fixed throughout these choice tasks (e.g., “current investors”, “international scalability”), the attribute levels (e.g., “external investors – unfamiliar to you”, “Easy”) were varied across choice tasks in a random manner (we performed a choice-based conjoint analysis with a reduced design). All attributes and attribute levels are described in Table 2.6.

CBC studies can suffer from three types of order effects (Chrzan, 1994): (1) the order of choice tasks, (2) the order of options in a choice task, and (3) the order of attributes within a choice task. To circumvent the effect of the choice task order, we created 800 different experimental designs. The choice tasks within each design are randomly ordered. To avoid the effect of the order of options in a given choice task, the two options within the 800 different experimental designs were randomly ordered within the respective choice tasks. To circumvent the effect of the order of attributes within a choice task, the order presented to participants is randomized across participants but kept stable within one participant. In addition, the participants are randomly allocated to one of the 800 experimental designs. Also, we conducted a pre-test with four experienced investors and four researchers who had previously conducted research on investor decision-making to confirm the face validity of both the attributes as well as the complexity and number of the choice tasks. The two fixed tasks were used to check the test-retest reliability of the participants’ choices in the study. By assessing the utilities from the 13 random choice tasks to predict the two fixed choice tasks, a proxy for test-retest reliability can be estimated.[5] In our study, this method leads to an 80% accuracy of correct classification.

Finally, to explore the importance attached to the different investment criteria, we performed multilevel logistic regression models. The investment decision made by the investment professionals serves as the binary dependent variable (1 if the investor chose the respective portfolio company; 0 if he did not), while the different attribute levels constitute our independent variables. We use a multilevel regression because our observations of investment decisions are nested and effects on multiple levels (particularly cross-level interactions) are evaluated at the same time. Two levels exist within our data: multiple decisions (level one) are nested within each individual (level two) and cannot be viewed as independent from each other.

Table 2.6: Attributes and attribute levels used in our conjoint analysis

This table describes and defines the attributes and attribute levels presented to participants in our conjoint analysis. We use a choice-based-conjoint (CBC) analysis, in which the participants are presented with investment opportunities and are asked to select the one company that better matches their preferences. The two companies are only described in terms of the attributes displayed in this table ("attributes") and only differ from each other in the respective specification of these criteria ("attribute levels").

Attribute	Attribute levels	Attribute description
(1) Profitability (3 levels, ordinal)	*1. Not profitable* *2. Break-even* *3. Profitable*	Describes the current profitability of the company.
(2) Revenue growth (4 levels, ordinal)	*1. 10% p.a.* *2. 20% p.a.* *3. 50% p.a.* *4. 100% p.a.*	Represents the company's average yearly revenue growth rate over the last years.
(3) Track record management team (3 levels, ordinal)	*1. None of them* *2. Some of them* *3. All of them*	Describes whether the management team has a relevant track record (e.g., industry experience or leadership experience).
(4) Current investors (3 levels, nominal)	*1. No other current external investors* *2. Other current external investor - Unfamiliar* *3. Other current external investor - Tier 1*	Describes the type of current investor, if any.
(5) Business model (4 levels, nominal)	*1. Lock-in* *2. Innovation-centered* *3. Low cost* *4. Complementary offering*	Describes the key focus of the business model of the company: 1. Lock-in: Business model that keeps customers attracted and "locked-in", having high switching costs for customers, which prevent them from changing to other providers. 2. Innovation-centered: Business model that offers innovation in the form of new technology, products or services. 3. Low cost: Business model focusing on reducing costs for customers for already existing products or services. 4. Complementary offering: Business model that bundles multiple goods or services to generate more value for customers.
(6) Value-added of product/service (3 levels, ordinal)	*1. Low* *2. Medium* *3. High*	Describes the value added for the customer through the product or service. Low value-added represents a marginal improvement (e.g., in cost-reduction or service quality), whereas high value-added represents significant improvements.
(7) International scalability (3 levels, ordinal)	*1. Easy* *2. Moderate* *3. Difficult*	Describes the difficulty of scaling the company internationally, in terms of the time and investment needed.

[5] The utility estimates from the 12 random choice task are computed with a hierarchical Bayesian model and then used as covariates in a logit regression on the holdout task choices.

2.3 Results

In this section, we present the results of our analysis in three steps. First, we show and discuss the relative importance of the different investment criteria. Then, we compare the importance of the decision criteria across investor types. Last, we apply a propensity score methodology as a robustness check.

2.3.1 Relative importance of investment criteria

Table 2.7 reports the results of our regression analysis. Model 1 uses the full sample while Models 2–6 consider each investor type separately. The coefficients indicate the importance investors attach to each criterion.

Model 1 shows that all included attribute levels significantly influence the decision of the investor ($p < 0.01$) except for the attribute level *current investors – unfamiliar*. Participants were found to be indifferent between the absence of current investors and the presence of current investors that are unfamiliar to them. However, investors significantly favor the presence of *reputable investors* over their lack of presence.

The results displayed in Table 2.7 also indicate which criteria are considered as most important by participants in their investment decisions. The effect sizes of the attribute levels for *revenue growth* are particularly large. Companies with a revenue growth rate of 100% p.a. have an odds-ratio (OR) of 4.86, indicating that these companies have a 4.86 times higher chance of a positive screening decision (selection) by an investor relative to companies with a 10% growth rate. Overall, *revenue growth* is the most important investment criterion for the participants in our sample. The second most important criterion is a high *value-added of the product/service* (OR of 4.25) and the third most important criterion is the *track record of the management team* where the odds-ratio of all team members having a relevant track record is estimated at 3.27, indicating a 3.27 times higher chance of a positive screening decision of the investors relative to companies with a management team without a relevant track record.

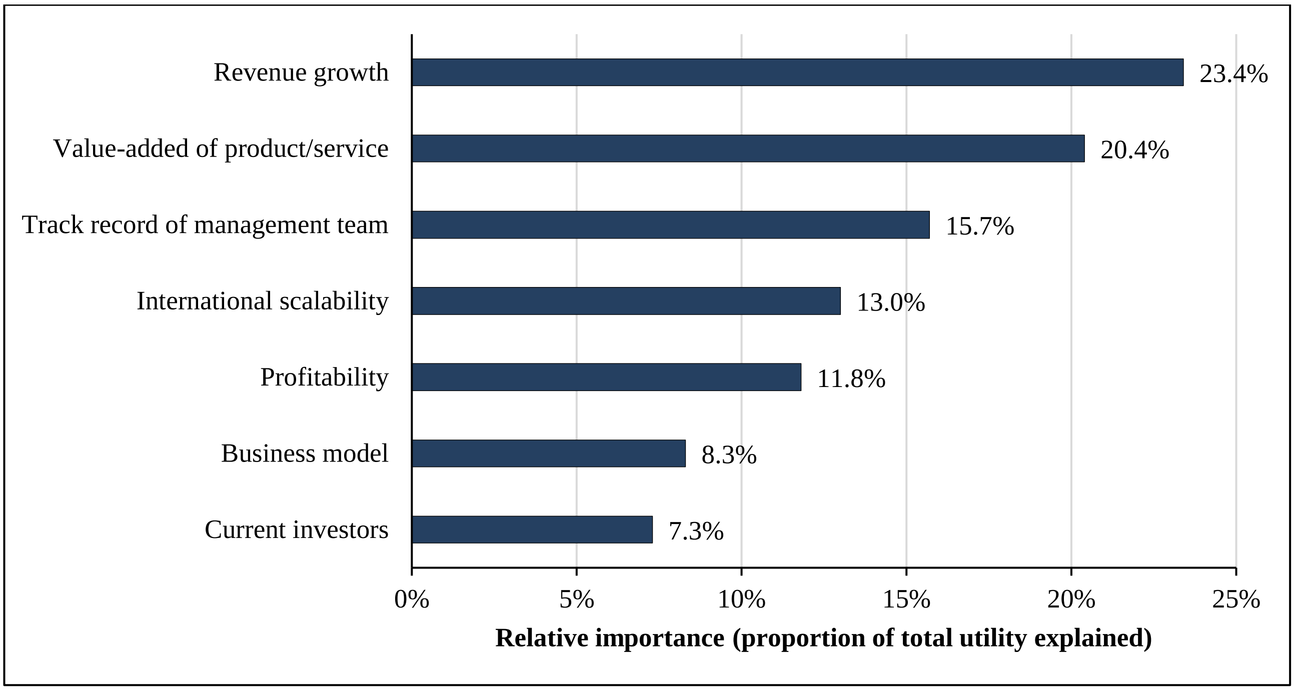
Table 2.7: Results of the conjoint analysis: main effects

This table shows the results of a clustered logistic regression with random intercepts and random slopes. The dependent variable is the preference of decision-maker and the independent variables are the attribute levels described in Table 2.4. Odds Ratios and standard errors (clustered at the decision-maker level) are displayed. Model 1 uses the full sample and shows that all attribute levels significantly influence the decision of the investor ($p < 0.01$) except for Current investor: external investors – unfamiliar. The coefficients indicate the importance investors attach to each criterion. For example, the effect sizes of the attribute levels for revenue growth are particularly large. Companies with a revenue growth rate of 100% p.a. have an odds-ratio of 4.86, indicating that these companies have a 4.86 times higher chance of a positive screening decision (selection) by an investor relative to companies with a 10% growth rate. In contrast, the effect sizes for profitability are comparatively small. With an odds ratio of 2.46, profitable companies have a 2.46 higher chance of being selected by a decision-maker than unprofitable companies. Models 2–6 consider each investor type separately and enable an initial comparison of the investment criteria's importance for each investor type. We consider family offices (FOs), business angels (BAs), venture capital funds (VCs), growth equity funds (GEFs), and leveraged buyout funds (LBOs). For example, the OR of 7.071 for LBOs with regard to profitability is considerably higher than the OR of 2.460 for the whole sample. This indicates that being profitable is a much more important criterion for LBOs then for other investor types. * < 0.10, ** $p < 0.05$, *** $p < 0.01$.

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Sample	**Full sample**	**FOs**	**BAs**	**VCs**	**GEFs**	**LBOs**
Variables	**OR (SE)**	**OR (SE)**	**OR (SE)**	**OR (SE)**	**OR (SE)**	**OR (SE)**
Profitability: break even	1.764 (0.086)***	2.311 (0.399)***	1.118 (0.379)	1.422 (0.090)***	2.069 (0.203)***	3.228 (0.500)***
Profitability: profitable	2.460 (0.139)***	4.213 (0.799)***	0.954 (0.331)	1.697 (0.116)***	3.303 (0.403)***	7.071 (1.218)***
(*reference group: not profitable*)						
Revenue growth: 20%	1.627 (0.080)***	1.440 (0.257)**	1.442 (0.425)	1.536 (0.105)***	1.895 (0.187)***	1.704 (0.255)***
Revenue growth: 50%	2.924 (0.164)***	1.805 (0.420)**	2.618 (0.953)***	3.080 (0.241)***	3.649 (0.390)***	2.324 (0.369)***
Revenue growth: 100%	4.863 (0.295)***	3.331 (0.706)***	5.150 (2.217)***	5.743 (0.493)***	4.909 (0.575)***	3.347 (0.581)***
(reference group: 10%)						
Management team: some team members	2.288 (0.110)***	2.480 (0.437)***	3.058 (1.043)***	2.177 (0.142)***	2.506 (0.251)***	0.914 (0.122)
Management team: all team members	3.268 (0.177)***	3.095 (0.537)***	4.401 (1.825)***	3.325 (0.240)***	3.898 (0.443)***	1.117 (0.167)
(reference group: no team member)						
Current investor: ext. investors - unfamiliar	1.038 (0.047)	0.887 (0.144)	0.778 (0.214)	1.042 (0.065)	1.153 (0.110)	2.349 (0.322)***
Current investor: ext. investors - tier 1	1.515 (0.077)***	1.243 (0.217)	0.990 (0.255)	1.828 (0.127)***	1.320 (0.143)**	2.178 (0.385)***
(reference group: no external investor)						
Business model: innovation-centered	1.687 (0.093)***	2.172 (0.438)***	1.669 (0.576)	2.079 (0.160)***	1.279 (0.140)**	1.037 (0.165)
Business model: lock-in	1.719 (0.094)***	1.634 (0.289)***	0.631 (0.227)	1.964 (0.142)***	1.576 (0.185)***	1.685 (0.276)***
Business model: complementary offering	1.271 (0.066)***	1.427 (0.267)*	0.663 (0.226)	1.354 (0.098)***	1.230 (0.132)*	1.179 (0.174)
(reference group: low cost)						
Value-added of product/service: medium	2.395 (0.116)***	2.659 (0.473)***	1.573 (0.444)	2.526 (0.167)***	2.054 (0.193)***	2.924 (0.474)***
Value-added of product/service: high	4.245 (0.233)***	4.795 (0.929)***	3.046 (0.776)***	4.713 (0.374)***	3.488 (0.357)***	4.696 (0.767)***
(reference group: low)						
International scalability: moderate	1.817 (0.083)***	1.395 (0.229)**	2.178 (0.384)***	1.833 (0.120)***	1.827 (0.163)***	2.133 (0.329)***
International scalability: easy	2.697 (0.138)***	2.186 (0.411)***	3.511 (1.214)***	2.891 (0.204)***	2.433 (0.239)***	3.167 (0.518)***
(reference group: difficult)						
N (decisions)	19,474	1,534	520	10,296	4,914	2,210
N (decision makers)	749	59	20	396	189	85

To further illustrate the weight attached to each criterion, we estimate the relative importance of each attribute following Franke et al. (2008). The values displayed in Figure 2.2 allow an assessment of how strong a change in an attribute's level does affect the total utility of a proposed company. The higher the value, the higher the contribution of the respective attribute to the company's total utility value. To enable a better comparison, the values are normalized so that the sum of all importance values yields 100. Overall, the chance of a positive screening decision is strongly affected by high values in the attributes of (1) revenue growth, (2) value-added of product/service, and (3) management track record; the design of the business model and the type of existing investors are relevant but are of lower importance. The same is true for the ease of scaling the company internationally and profitability.

Figure 2.2: Relative importance of attributes



Notes: Calculated based on the coefficients of the main model (Table 5). Reading example: With a relative importance of 23.4%, investors consider revenue growth to be nearly three times as important as the criterion current investors (relative importance: 7.3%). This value also signifies that the criterion revenue growth accounts for 23.4% of the decision maker's total utility

2.3.2 Differences across investor types

Table 2.7 also includes a dedicated model for each investor type in which we perform a subsample analysis (Models 2–6). The odds ratios enable an initial comparison of the investment criteria's importance for each investor type and provide insights on the relevance of each attribute. For example, the OR of 7.071 for participants from LBOs with regard to profitability is considerably higher than the OR of 2.460 for the whole sample. This indicates that being profitable is a much more important criterion for LBOs than for other investor types. However, a comparison of the ORs does not shed light on whether these differences across investor types are statistically significant.

To address this issue, Table 2.8 estimates separate regressions where the importance of investment criteria for each investor type is tested against the rest of the sample. For example, Model 1 compares the effect of FOs against the combined group of BAs, VCs, GEFs, and LBOs. As such, the coefficients displayed are interaction effects that enable a statement on whether the importance of each criterion differs significantly from the rest of the sample, enabling statements as to where each investor type stands out from the other investors. The following paragraphs refer to the respective models for each investor type.

Investment criteria of family offices (FOs)

Model 1 of Table 2.8 compares FO's investment criteria to the investment criteria of the other investor types. The results show that FOs differ with regard to the importance attached to profitability and revenue growth. In particular, FOs consider profitability significantly more important than other investor types and attach significantly less importance to high levels of revenue growth. No significant differences emerge regarding the remaining investment criteria.

An explanation for the distinct preference of profitability lies in the fact that financial goals are likely to be different for FOs relative to other investors. While the return on investment is naturally important, it is intermingled with objectives of wealth preservation. FOs, whose goals are determined by the families to which they belong or for which they work, are often conservative and risk-averse and thus more reluctant to pursue high-risk investments (Wessel et al., 2014). By undertaking risky decisions, the managers of FOs risk losing family wealth and jeopardize the financial and social well-being of future family generations. Therefore, they are more concerned with the conservation of irreplaceable capital, often accumulated over generations, rather than potential high returns. Indeed, the mission of FOs is to protect and preserve assets for future generations. A survey by Bloomberg (2017) finds that the main objective of FOs is intergenerational wealth management. Since companies with poor profitability are associated with a high risk of bankruptcy (Agarwal and Taffler, 2008), FOs will consider such investments to be high-risk investments. Therefore, they will tend to avoid such investments, explaining our findings.

Similarly, while current profitability reflects an investment associated with lower risk, high growth potentially incurs uncertainty, as it exposes entrepreneurial companies to additional challenges and risks (e.g., from entering new markets and hiring new employees) (Perez-Quiros and Timmermann, 2000). Adding to this, our descriptive statistics indicate that FOs are not as resourceful as other PE investors. From a resource-based perspective, FOs are thus disadvantaged with regard to monitoring and providing support to their portfolio companies. This disadvantage is particularly relevant in the case of high-growth companies. Monitoring and supporting high-growth companies is typically very challenging and resource-intensive.

Table 2.8: Results of the conjoint analysis with comparison across two types of investors

This table shows the results of a clustered logistic regression with random intercepts and random slopes. The dependent variable is the preference of decision-maker and the independent variables are the attribute levels described in Table 2.4. Logits and standard errors (clustered at the decision-maker level) are displayed. Each attribute level is interacted with the respective investor category. For example, in Model 1 every attribute level is interacted with a dummy variable that takes a value of 1 if the respective decision-maker worked in a family office, and 0 if not. The main effects are included in the estimation but are omitted for reasons of brevity so that the coefficients displayed here only refer to interaction effects. However, the main effects are qualitatively similar to the effects displayed in Model 1 of Table 2.5. Focusing on the interaction effects enables us to identify significant differences between each investor type vs. the remaining investor types. For example, the results of Model 1 show that family offices attribute significantly more importance to "Profitability: profitable" in comparison to the rest of the sample. In contrast, "Profitability: profitable" is significantly less important to venture capital funds when compared with the rest of the sample. We consider family offices (FOs), business angels (BAs), venture capital funds (VCs), growth equity funds (GEFs), and leveraged buyout funds (LBOs). * < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Sample	**FOs vs. rest**	**BAs vs. rest**	**VCs vs. rest**	**GEFs vs. rest**	**LBOs vs. rest**
Interactions	**Logit (SE)**	**Logit (SE)**	**Logit (SE)**	**Logit (SE)**	**Logit (SE)**
Profitability: break even	0.311 (0.171)*	-0.316 (0.319)	-0.467 (0.091)***	0.200 (0.105)*	0.631 (0.156)***
Profitability: profitable	0.606 (0.200)***	-0.801 (0.322)**	-0.812 (0.106)***	0.368 (0.131)***	1.128 (0.171)***
Revenue growth: 20%	-0.114 (0.171)	0.179 (0.265)	-0.160 (0.091)*	0.181 (0.104)*	0.016 (0.144)
Revenue growth: 50%	-0.505 (0.211)**	0.181 (0.364)	0.057 (0.106)	0.267 (0.117)**	-0.315 (0.158)**
Revenue growth: 100%	-0.390 (0.192)**	0.400 (0.396)	0.292 (0.112)***	-0.016 (0.126)	-0.482 (0.168)***
Management team: some team members	0.106 (0.173)	0.525 (0.321)	-0.142 (0.090)	0.106 (0.104)	-0.167 (0.131)
Management team: all team members	-0.043 (0.169)	0.568 (0.389)	-0.001 (0.102)	0.213 (0.121)*	-0.373 (0.146)**
Current investor: external investors - unfamiliar	-0.156 (0.159)	-0.178 (0.286)	-0.007 (0.088)	0.128 (0.102)	-0.025 (0.134)
Current investor: external investors - tier 1	-0.202 (0.167)	-0.299 (0.256)	0.371 (0.095)***	-0.200 (0.116)*	-0.501 (0.167)***
Business model: innovation-centered	0.295 (0.194)	0.230 (0.347)	0.403 (0.104)***	-0.388 (0.120)***	-0.587 (0.163)***
Business model: lock-in	-0.038 (0.159)	-0.841 (0.350)**	0.236 (0.102)**	-0.136 (0.125)	-0.075 (0.164)
Business model: complementary offering	0.142 (0.180)	-0.478 (0.330)	0.096 (0.102)	-0.064 (0.119)	-0.126 (0.144)
Value-added of product/service: medium	0.131 (0.165)	-0.232 (0.308)	0.094 (0.091)	-0.224 (0.102)**	0.173 (0.156)
Value-added of product/service: high	0.154 (0.179)	-0.121 (0.268)	0.181 (0.101)*	-0.284 (0.109)***	0.052 (0.154)
International scalability: moderate	-0.275 (0.177)	0.399 (0.209)*	0.004 (0.092)	-0.009 (0.101)	0.137 (0.158)
International scalability: easy	-0.214 (0.189)	0.483 (0.352)	0.115 (0.099)	-0.156 (0.110)	0.123 (0.163)
N (decisions)	19,474	19,474	19,474	19,474	19,474
N (decision makers)	749	749	749	749	749

Investment criteria of business angels (BAs)

Model 2 of Table 2.8 focusses on BAs. A particularity of BA's investment decisions is that they focus less on profitability than other investors. An explanation is that BAs primarily invest in early-stage companies (Hellmann and Thiele, 2015), which involves a comparatively high degree of uncertainty. In these companies, profitability is of minor importance as they are often not mature enough to achieve profits. Having achieved profitability, in turn, is a sign of a healthy business model and a strong competitive position. Typical companies targeted by BAs still need to achieve legitimacy by proving that their products fulfill market needs and provide value to their customers. In this regard, revenue growth can be perceived as a sign of market acceptance.

Additionally, BAs prefer not to invest in companies with business models that keep customers “locked-in”, such as those having high switching costs to prevent customers from changing to other providers. Relative to other types of investors, BAs disfavor locked-in business models for innovation-centered or low-cost business models (i.e., focusing on reducing costs for customers for already existing products or services).

Investment criteria of venture capital funds (VCs)

Model 3 of Table 2.8 focusses on the investment criteria of VCs. Like BAs and in contrast to the other investor types in our sample, VCs attribute significantly less importance to profitability. Also, VCs attribute significantly more importance to high levels of revenue growth. These findings are both in line with prior literature, in which VC investments are generally characterized as high risk and high growth (Ueda, 2004). For example, Puri and Zarutskie (2012) show that VCs invest in companies with no immediate revenues and focus on scalability instead of profitability. In our results, this higher scalability is reflected in VC’s increased interest in revenue growth. An explanation is that VCs need to deliver returns to their partners over a relatively short period, which incentivizes them to take riskier investments. The short investment horizon of VC funds and the investors behind them exacerbate the short-termism of general partners (Kaplan and Stromberg, 2004), who are asked to provide high returns by capital providers. All else being equal, high returns are more difficult to achieve in already profitable companies, whereas the higher risk of entrepreneurial companies is associated with higher chances of high growth rates. Also, the incentives that principals (limited partners) set for fund managers (general partners) (i.e., to select investments with the potential to generate high returns) are paralleled at the individual level. Similar to mutual fund managers, their professional identity stems from their reputation in the market, which is to a large degree gained and sustained through their investment track record (Chevalier and Ellison, 1999; Kempf and Ruenzi, 2007). Fund managers who do not provide high returns to their investors will find it hard to secure further funding and suffer from a reduced labor market value. In addition to monetary returns, other motivations for VC investment professionals involve status and the desire to outcompete their peers. These motivations are reflected in the characteristics of the entrepreneurial companies that they seek. A company with high current profitability does not represent the ideal setting for possibly outperforming others and gaining popularity as a fund manager.

The findings also show that VCs have a preference for funding companies in which tier 1 investors are present. The presence of reputable investors is a key aspect in VC investments as it allows VC funds to command a premium from future entrepreneurs (Hsu, 2004) and makes future investment fundraising easier (Megginson and Weiss, 1991; Nahata, 2008). Moreover, VCs with broader networks obtain better financial returns (Hochberg et al., 2007) and mitigate risks (Lerner, 1994).

Finally, the results show that VCs prefer innovation-centered business models. Again, this is in line with a strategy that is overall more risk-prone and focusses on a high-risk high-reward tradeoff.

Investment criteria of growth equity funds (GEFs)

Model 4 of Table 2.8 focusses on the investment criteria of GEFs. Like FOs and in contrast to BAs and VCs, GEFs attach higher importance to portfolio companies' profitability. This corresponds to the results of Ritter (2015), who describes that GEFs frequently invest in companies that are already profitable. Regarding revenue growth, our results show a general preference for revenue growth, as GEFs consider a revenue growth of 20% or 50% to be more important than other investor types do. Interestingly, GEFs do not seem to rate a very high revenue growth of 100% to be more important than other investors do. This is a difference to VCs, which differ from other investors regarding the importance attached to very high levels of revenue growth.

Another peculiarity of GEFs is that they consider it comparably important that all management team members have a relevant track record. Also, GEFs attach less importance to the presence of reputable investors. An explanation is that the presence of other investors can generate severe conflicts of interest and agency problems. For example, freeriding behavior can occur, incurring costs associated with monitoring or sanctioning opportunistic behavior (Jensen and Meckling, 1976). The costs associated with co-investing are higher in the presence of a reputable investor. For example, co-investing generally leads to a higher likelihood of difficult negotiations between the parties involved (Fried and Hisrich, 1995).

GEFs attach less importance than other investor types to innovation-centered business models and the value-added of a portfolio company's products and services. An explanation could be that companies with innovation-centered business models as well as high-value products may serve niche markets and are therefore difficult to grow and scale.

Investment criteria of leveraged buyout funds (LBOs)

Model 5 of Table 2.8 explores the investment criteria of LBOs in contrast to the other investor types. Like FOs and GEFs, LBOs attach relatively higher importance to portfolio companies' profitability. The effect is very pronounced and highly significant. In contrast, LBOs attach significantly lower importance to revenue growth than other investor types. Regarding the importance of profitability and revenue growth, LBOs hence present the opposite investor type to VCs. While VCs focus on a high scalability of companies (Puri and Zarutskie, 2012), this indicates that scalability may not be of interest to LBOs. Instead, LBOs are more prone to invest in already profitable companies, as they are a less risky investment.

LBOs attach less importance to the management team as compared to other types of investors. This might be due to their tendency to replace management teams that they see unfit (Kaplan and Stromberg, 2009). Hence, the current management team is considered less important. Like GEFs, LBOs pay less attention to the presence of reputable investors. As discussed in the previous section, the presence of reputable investors might make it more difficult for LBOs to pursue their own goals. Finally, similar to GEFs, LBOs attach lower importance to innovation-centered business models.

2.3.3 Robustness tests and further analyses

To test the robustness of our results and to further explore these results, we perform a set of robustness checks and additional analyses, summarized in Table 2.9. In our main analysis, we compare each investor type against all other investor types included in our sample. While this comparison highlights the peculiarities of the respective investor's investment criteria in contrast to the other investor types, we now investigate differences in the importance of investment criteria in selected pairs of investor types. This more specific analysis allows us to explore differences between specific investor types in a more nuanced way that may have been masked in the main analysis. Specifically, we conduct a pairwise comparison of the following investor types: FOs vs. VCs (Model 1), FOs vs. BAs (Model 2), GEFs vs. LBOs (Model 3), and VCs vs. GEFS and LBOs (combined).

In addition, we use propensity score matching to make subsamples comparable in terms of investor and investment professional characteristics. As these differences might influence investment decisions, we use propensity score matching (PSM) to reduce the potential bias and to further improve our comparisons across investor types. We match individuals from different investor types according to their individual characteristics (Table 2.4, panel C). We use a k-nearest neighbor (KNN) approach with 1-to-1 matching, which matches pairs of observations that are the most related.

Comparison between family offices (FOs) and venture capital funds (VCs)

Model 1a (Table 2.9) compares the investment criteria of FOs (N = 59) and VCs (N = 396). The results show that FOs attach higher importance to profitability while they attach lower importance to revenue growth. Both findings are in line with the results reported in our main analysis (Table 2.8, Model 1), underlining their robustness. Also, both results hold when utilizing PSM, reducing the sample to 59 FOs and 59 VCs that are the most similar to these FOs (Model 1b).

In contrast to our main analysis, the results further show that, compared with VCs, FOs attach significantly lower importance to the presence of reputable investors in the portfolio company. This effect can be attributed to VCs' high preference for the presence of reputable investors as a signal certifying company quality (Hochberg et al., 2007; Hsu, 2004). In contrast to VCs, FOs may be more reluctant to partner with prominent investors because the costs associated with co-investing are higher for FOs in the presence of a reputable investor. For example, co-investing generally leads to a higher likelihood of difficult negotiations between the parties involved (Fried and Hisrich, 1995). If the co-investing party is a reputable investor, the FO will have a weaker negotiation position that discourages co-investing. Additionally, it is more difficult for a FO to sanction the opportunistic behavior of a reputable investor compared to more unknown investors. Also, reputable investors are more likely to be active and shape their portfolio companies Cumming and Zhang (2019) as well as introduce high-growth policies to accelerate faster public markets that are incoherent with the capital preservation goals of FOs. Notice, however, that this effect does not persist when reducing the sample of VCs via PSM (Model 1b).

Comparison between family offices (FOs) and business angels (BAs)

Model 2a (Table 2.9) compares the investment criteria of FOs (N = 59) and BAs (N = 20). Both investor types share similarities, as they are non-intermediated, tied to personal/family wealth, possibly confounded with non-financial motives, and represent the smallest investor types in our sample (with regard to assets under management). We find that FOs put a comparatively higher emphasis on profitability and a lower emphasis on revenue growth. While these differences (especially with regard to the importance of revenue growth) are not as pronounced, they correspond to the results of our main analysis. Model 2b reports the results of the regression performed after PSM. The drop in significance can be at least partially attributed to the decreased sample sizes (N = 79 for Model 2a, N = 40 for Model 2b). Further differences emerge with regard to the importance of selected business models and international scalability. FOs have a higher preference for lock-in business models than BAs. This higher preference is mainly due to BAs aversion against lock-in business models, as shown in the main analysis (Table 2.8, Model 2). Similarly, the main analysis shows that BAs have a general preference for higher international scalability. The results remain qualitatively similar when reducing the sample via PSM (Model 2b). Overall, these results allude to different risk-taking behavior, with FOs being more risk-averse and BAs being more risk-prone. This is similar to the results obtained when comparing FOs to VCs.

Comparison between growth equity funds (GEFs) and leveraged buyouts (LBOs)

Model 3a (Table 2.9) compares the investment criteria of GEFs (N = 189) and LBOs (N = 85). GEFs and LBOs constitute investor types that are particularly crucial in later-stage financing and are often treated as the same group of investors (e.g., Gompers et al., 2016a; Ritter, 2015). Indeed, our main analysis suggests that GEFs and LBOs are rather similar in their investment preferences. However, the more nuanced robustness checks uncover differences between both investor types when comparing them directly.

Major differences between GEFs and LBOs exist with regard to the importance of profitability as an investment criterion. While GEFs attach less importance to high levels of profitability, high profitability is crucial to LBOs. This difference was not apparent in our main analyses, as GEFs attach higher importance to profitability than all other investor types, which is mainly driven by VCs. In addition, the results show that GEFs attach higher importance to the management team's track record and lower importance to the value-added of the portfolio company's product or service than LBOs. Both effects are in line with the results of the main analysis. Also, utilizing PSM (Model 3b) to produce a more robust comparison shows that the results remain similar.

Comparison between venture capital funds (VCs) and growth equity funds (GEFs) plus leveraged buyouts (LBOs)

VCs, GEFs, and LBOs represent the major investor types in our sample. Gompers et al. (2016a) describe that considerable differences in the behavior between VCs on the one side and the GEFs and LBOs should exist. We explore these differences in Model 4a (Table 2.9), which compares the investment criteria of VCs (N = 396) to GEFs and LBOs combined (N = 274). However, the results are largely in line with the results of the main model. This is not surprising, as the sample used here (N = 670) covers 89% of the investment professionals in our entire sample (N = 749). For example, VCs put less emphasis on profitability and significantly more emphasis on high revenue growth. They also attach higher importance to the presence of reputable investors, innovation-centered business models, and a higher value-added of the company’s product or services. The results remain similar when reducing the sample using PSM (Model 4b), confirming the robustness of our results.

Table 2.9: Results of the conjoint analysis with comparisons of specific investor types without and with propensity score matching (PSM)

In this table, we focus on specific comparisons between selected investor types. The table is constructed in the same way as Table 2.6. The table shows the results of a clustered logistic regression with random intercepts and random slopes. The dependent variable is the preference of decision-maker and the independent variables are the attribute levels described in Table 2.4. Logits and standard errors (clustered at the decision-maker level) are displayed. Each attribute level is interacted with the respective investor category. For example, in Model 1a every attribute level is interacted with a dummy variable that takes a value of 1 if the respective investor worked in a family office, and 0 if the respective investor worked for a venture capital fund. The main effects are included in the estimation but are omitted for reasons of brevity so that the coefficients displayed here only refer to interaction effects. However, the main effects are qualitatively similar to the effects displayed in Table 2.5. Focusing on the interaction effects enables us to identify significant differences between each investor type vs. the remaining investor types. Investors working for certain investor types might significantly differ with regard to individual characteristics. As these differences might influence investment decisions, we use propensity score matching (PSM) to reduce this potential bias. We match individuals from different investor types according to their individual characteristics (Table 2.4, panel C). We use a k-nearest neighbor (KNN) approach with 1-to-1 matching, which matches a pair of observations that are the most related. We consider family offices (FOs), business angels (BAs), venture capital funds (VCs), growth equity funds (GEFs), and leveraged buyout funds (LBOs). * < 0.10, ** p < 0.05, *** p < 0.01.

Model	**(1a)**	**(1b)**	**(2a)**	**(2b)**	**(3a)**	**(3b)**	**(4a)**	**(4b)**
PSM	**No PSM**	**KNN 1:1 PSM**	**No PSM**	**KNN 1:1 PSM**	**No PSM**	**KNN 1:1 PSM**	**No PSM**	**KNN 1:1 PSM**
Sample	**FOs vs. VCs**	**FOs vs. VCs**	**FOs vs. BAs**	**FOs vs. BAs**	**GEFs vs. LBOs**	**GEFs vs. LBOs**	**VC vs. GEFs+LBOs**	**VC vs. GEFs+LBOs**
Interactions	**Logit (SE)**	**Logit (SE)**	**Logit (SE)**	**Logit (SE)**	**Logit (SE)**	**Logit (SE)**	**Logit (SE)**	**Logit (SE)**
Profitability: break even	0.513 (0.175)***	0.459 (0.242)*	0.579 (0.352)*	0.260 (0.407)	-0.417 (0.175)**	-0.539 (0.200)***	-0.495 (0.098)***	-0.506 (0.104)***
Profitability: profitable	0.944 (0.203)***	0.963 (0.257)***	1.314 (0.362)***	1.145 (0.413)***	-0.728 (0.201)***	-0.856 (0.223)***	-0.874 (0.116)***	-0.926 (0.122)***
Revenue growth: 20%	-0.033 (0.177)	-0.100 (0.240)	-0.254 (0.304)	-0.406 (0.348)	0.133 (0.164)	0.188 (0.186)	-0.183 (0.098)*	-0.120 (0.108)
Revenue growth: 50%	-0.499 (0.218)**	-0.650 (0.286)**	-0.625 (0.408)	-0.927 (0.446)**	0.486 (0.179)***	0.677 (0.206)***	-0.026 (0.111)	0.010 (0.120)
Revenue growth: 100%	-0.504 (0.200)**	-0.593 (0.290)**	-0.728 (0.429)*	-0.759 (0.476)	0.419 (0.192)**	0.481 (0.232)**	0.283 (0.120)**	0.330 (0.129)**
Management team: some team members	0.161 (0.178)	0.172 (0.224)	-0.410 (0.355)	-0.484 (0.407)	0.092 (0.156)	0.167 (0.189)	-0.106 (0.095)	-0.155 (0.103)
Management team: all team members	-0.039 (0.174)	-0.151 (0.242)	-0.578 (0.414)	-0.450 (0.451)	0.610 (0.191)***	0.755 (0.234)***	0.018 (0.112)	-0.004 (0.121)
Current investor: ext. investors - unfamiliar	-0.142 (0.165)	0.009 (0.228)	0.024 (0.316)	-0.167 (0.382)	0.250 (0.153)	0.249 (0.179)	-0.040 (0.095)	-0.004 (0.105)
Current investor: ext. investors - tier 1	-0.365 (0.172)**	-0.316 (0.227)	0.102 (0.293)	0.184 (0.363)	0.187 (0.173)	0.136 (0.195)	0.377 (0.106)***	0.334 (0.114)***
Business model: innovation-centered	0.080 (0.200)	0.075 (0.260)	0.045 (0.384)	0.361 (0.519)	0.235 (0.187)	0.314 (0.214)	0.544 (0.111)***	0.507 (0.121)***
Business model: lock-in	-0.150 (0.165)	-0.099 (0.242)	0.771 (0.373)**	0.989 (0.430)**	-0.037 (0.192)	-0.069 (0.231)	0.205 (0.113)*	0.174 (0.123)
Business model: complementary offering	0.084 (0.187)	0.153 (0.270)	0.587 (0.365)	1.039 (0.416)**	0.069 (0.170)	0.099 (0.211)	0.107 (0.109)	0.087 (0.118)
Value-added of product/service: medium	0.083 (0.170)	0.146 (0.221)	0.340 (0.340)	0.630 (0.404)	-0.325 (0.173)*	-0.498 (0.202)**	0.119 (0.098)	0.151 (0.106)
Value-added of product/service: high	0.054 (0.187)	0.251 (0.260)	0.249 (0.308)	0.512 (0.385)	-0.266 (0.172)	-0.336 (0.198)*	0.231 (0.108)**	0.279 (0.121)**
International scalability: moderate	-0.250 (0.182)	-0.256 (0.236)	-0.626 (0.262)**	-0.834 (0.327)**	-0.129 (0.175)	-0.105 (0.195)	-0.034 (0.098)	0.001 (0.108)
International scalability: easy	-0.250 (0.195)	-0.416 (0.246)*	-0.663 (0.388)*	-0.749 (0.446)*	-0.234 (0.182)	-0.189 (0.212)	0.112 (0.106)	0.096 (0.114)
N (decisions)	11,830	3,068	2,054	1,040	7,124	4,420	17,420	14,248
N (decision makers)	455	118	79	40	274	170	670	548
Sample	59 FOs vs. 396 VCs	59 FOs vs. 59 VCs	59 FOs vs. 20 BAs	20 FOs vs. 20 BAs	189 GEFs vs. 85 LBOs	85 GEFs vs. 85 LBOs	396 VCs vs. 274 GEFs+LBOs	274 VCs vs. 274 GEFs+LBOs

2.4 Conclusions

PE investors place a heavy emphasis on their ability to select promising companies. In spite of the large interest in the decision-making of PE investors, this study is among the first to assess the investment criteria of these investors. While there is an established literature on the characteristics and behavior of specific types of investors, a broader perspective is underdeveloped. We compare the investment criteria of different types of investors using a large-scale conjoint analysis of 19,474 screening decisions by 749 private equity investors. The conjoint experiment enables a better understanding of the investment criteria of investors and allows a comparison of these criteria across investor types. We distinguish FOs, BAs, VCs, GEFs, and LBOs.

In Table 2.10, we provide a summary of the many insights of the paper. For instance, we find that the management team is an important investment criterion for our participants. However, we also find that investors rate revenue growth and the value-added provided by the company's product or service to be more important than the management team's track record. The importance attached to the management team does not significantly vary across investors. Second, we find two opposite views with regard to profitability. While the investment criteria of FOs, GEFs, and LBOs are centered on highly profitable companies, BAs and VCs pay less attention to the current profitability of their targets and instead focus on their scalability. Third, our study sheds light, for the first time, on the investment criteria of FOs and finds that, relative to the average of other PE investors, FOs attribute greater importance to the current profitability of portfolio companies but less importance to their revenue growth. An explanation is that by undertaking risky decisions, the managers of FOs risk losing family wealth and jeopardize the financial and social wellbeing of future family generations. They are therefore more concerned with the conservation of irreplaceable capital through investments in already profitable companies, rather than bearing the risk and potentially high returns of high-growth companies.

Table 2.10: Summary of the main findings

This table provides a summary of our main findings. The attributes used in our conjoint experiment are ranked according to their relative importance (also displayed in Figure 2.2). To calculate the relative importance of each attribute, we use the range between the attribute level with the lowest utility value and the level of the respective attribute with the highest utility based on the coefficients of the main model (Table 2.7). This allows an assessment of how strong a change in an attribute's level does affect the total utility of a proposed company. This range is then divided by the sum of all ranges for each decision-maker, showing the relative importance of the attributes. The values displayed in column 3 represent the mean values across all investor types', while columns 4 and 5 display the investor type with the lowest and highest importance. The final column contains a brief qualitative summary of the main findings of our comparative analyses and is based on Table 2.8. All attributes are defined in Table 2.6. We consider family offices (FOs), business angels (BAs), venture capital funds (VCs), growth equity funds (GEFs), and leveraged buyout funds (LBOs).

Rank	Attribute	Relative importance	Lowest relative importance	Highest relative importance	Main results (qualitative summary)
1	Revenue growth	23.4%	13.8% (LBOs)	26.3% (VCs)	Major differences across investor types: less important to FOs, LBOs and more important to VCs, GEFs.
2	Value-added of product/service	20.4%	15.3% (BAs)	22.8% (FOs)	Minor differences across investors: less important to GEFs.
3	Track record of management team	15.7%	4.8% (LBOs)	22.1% (BAs)	Minor differences across investors: less important to LBOs.
4	International scalability	13.0%	10.4% (FOs)	17.7% (BAs)	No major differences in importance across investor types.
5	Profitability	11.8%	5.6% (BAs)	31.9% (LBOs)	Major differences across investor types: less important to BAs, VCs and more important to FOs, GEFs, LBOs.
6	Business model	8.3%	7.1% (LBOs)	10.3% (FOs)	Major differences across investor types. Less important to GEFs, LBOs and more important to VCs.
7	Current investors	7.3%	5.0% (BAs)	20.4% (LBOs)	Major differences across investor types: less important to GEFs, LBOs and more important to VCs.

Chapter 3

A personality perspective on business angel syndication

The decision to syndicate investments in entrepreneurial finance has been explained through financial, networking, and resource-based perspectives. We posit that a personality perspective exists next to these three perspectives and hypothesize that the personality of business angels influences syndication behavior. Using data from 3,234 syndication decisions of 1,348 business angels, we find evidence for some of our predictions. By measuring personality through a comprehensive language analysis based on digital footprints in Twitter statements of business angels, we show that extraversion makes syndication more likely, whereas conscientiousness reduces the likelihood of syndication. Several sensitivity analyses underline the robustness of our main results. Further exploratory analyses assess the relationship between personality and syndicate composition as well as that between personality and venture success. Our study contributes to the entrepreneurial finance literature by adding and validating a new perspective to explain syndication behavior. In addition, our study contributes to research on the personality of business angels.

This chapter is based on

Block, J., Fisch, C., Obschonka, M., Sandner, P., 2019. A personality perspective on business angel syndication. *Journal of Banking & Finance*, 100, 306–327.

3.1 Introduction

Business angels (BAs) are an important source of funding for innovative start-ups and an important driver for new venture development and innovation (Croce et al., 2018; Dutta and Folta, 2016; Kim and Wagman, 2016; Lerner, 1998). They not only provide badly needed financial capital in the early stages of new venture development but also help start-ups with their management know-how and network access (Dutta and Folta, 2016; Kerr et al., 2014; Prowse, 1998). BAs can invest alone or through an investment syndicate together with other investors. While syndication is a topic that has received considerable attention in the entrepreneurial finance literature, little is known about BAs' syndication decisions. Specifically, the prior literature's focus is almost exclusively on venture capital (VC) firms, and the decision to syndicate has been explained from financial, networking, and resource-based perspectives (e.g., Bygrave, 1987; Dimov and Milanov, 2010; Lockett and Wright, 2001; Manigart et al., 2006; Sorenson and Stuart, 2001; Ter Wal et al., 2016).

We argue that in addition to these three perspectives, a personality perspective on BA syndication exists. BAs invest their own money and act as individual investors. Their personality plays an important role with regard to their preferences and investment styles. Based on psychology literature on inter-individual differences in personality traits (Digman, 1990; John et al., 2008) and their important effects on decision-making and investment behavior (e.g., Corter and Chen, 2006; Durand et al., 2008; Gambetti and Giusberti, 2012), we hypothesize that the BA's personality influences the choice to invest alone or as part of a syndicate. Using the Big Five personality traits (extraversion, conscientiousness, openness, agreeableness, and neuroticism) as a comprehensive personality framework, we hypothesize that BAs high in extraversion, agreeableness, or neuroticism are more likely to engage in syndication. In contrast, we assume that BAs high in openness and conscientiousness are less likely to engage in syndication.

Using data from 3,234 syndication decisions of 1,348 BAs, we find support for some of our predictions. Measuring personality via a novel but validated method of language analysis that analyses BAs' posts on Twitter to infer their personality structure, we show that extraversion makes syndication more likely, whereas conscientiousness reduces the likelihood of syndication. Openness, agreeableness, and neuroticism do not show statistically significant effects. Multiple sensitivity analyses underline the robustness of our results. Furthermore, we explore the effects of BA personality on other important outcomes, such as syndicate characteristics and investment success. These exploratory analyses show that a BA's personality has an influence on the composition of the syndicate but seems to be unrelated to venture success, opening up many avenues for future research.

Our results contribute to the entrepreneurial finance literature in three ways. First, we contribute to the syndication literature (e.g., Dimov and Milanov, 2010; Duxbury et al., 1996; Lerner, 1998; Sorenson and Stuart, 2001; Wright and Lockett, 2003) by showing that a BA's personality plays an important role in the decision to form a syndicate or not. To date, the personality of investors such as BAs has not been considered a factor driving the syndication decision. Our study introduces this personality perspective to the syndication literature. Second, our study contributes to the literature on BAs (e.g., Croce et al., 2018; Dutta and Folta, 2016; Kim and Wagman, 2016). We show that BAs are a heterogeneous group and that personality plays a crucial role in their behavior as investors. So far, research has focused mainly on socio-demographic and human capital characteristics describing the heterogeneity of BAs as a group (e.g., Becker-Blease and Sohl, 2011). Third, our study makes a methodological contribution by showing that BA personality measured through Tweets correlates with the BA investment behavior. Such methods have been shown to deliver remarkably accurate information about actual personality features (Boyd and Pennebaker, 2017; Kosinski et al., 2013). In particular, using Twitter data allows us to access groups of individuals who have been very hard to reach and include in empirical studies (Lee et al., 2017; Obschonka et al., 2017; Obschonka and Fisch, 2018). BAs fall into this category. This way, our study opens up a new research agenda for research using data from social media such as Twitter to describe entrepreneurial finance investors and predict their investment behavior.

3.2 Literature review

3.2.1 Benefits of syndication for BAs

Based on insights from VC firms, prior research offers three perspectives on BA syndication (e.g., De Vries and Block, 2011; Lerner, 1998; Lockett and Wright, 2001; Manigart et al., 2006).

First, the *financial perspective* (Dimov and Milanov, 2010; Manigart et al., 2006) maintains that syndication allows investors to finance a larger number of ventures. This way, the investor is able to diversify his or her portfolio, reducing the investor's investment risk. Syndication is a means to achieve optimal portfolio diversification (e.g., van Osnabrugge, 1998). Without syndication, single investments will account for a relatively large investment share, hence leading to higher risk exposure. Additionally, investors gain more flexibility with regard to liquidity by spreading their money over more investments. This argument is particularly true for BAs who typically have lower amounts of money to invest than corporate investors (e.g., Croce et al., 2018; van Osnabrugge, 2000). Another financial perspective argument for syndication relates to the increased exit opportunities available through syndication. BAs typically only finance the first rounds of investment in the venture financing cycle (e.g., Croce et al., 2018). Through syndication with VC firms or strategic investors, BAs increase their chances of a successful exit. If the venture turns out to be a success, BAs can sell their equity stake to their co-investors.

Second, the *networking perspective* postulates that syndication is a result of investor networks and is an important prerequisite to securing future deal flow (Bygrave, 1987; Dimov and Milanov, 2010; Sorenson and Stuart, 2001). In the entrepreneurial finance community, it is expected that invitations to join a syndicate will be reciprocated. Hence, BAs secure a sufficient deal flow, which allows them to spread their investment risk and generate enough attractive investment opportunities.

Third, the *resource-based* or *value-added perspective* argues that syndication is a way for different investors to share (complementary) knowledge and assets and thereby create value for the start-ups and the investment syndicate (Cumming et al., 2005; Dimov and Milanov, 2010; Lockett and Wright, 2001; Ter Wal et al., 2016). For example, investment partners can provide additional knowledge on an investment target during due diligence, thereby improving the overall quality of the final investment decision and preventing adverse selection (Lerner, 1998). Previous research indicates that VCs conduct significantly more due diligence than BAs because they typically have more experience and resources to carry out thorough due diligence (van Osnabrugge, 2000). Syndication is a way to overcome this disadvantage for BAs.

3.2.2 Disadvantages and costs of syndication for BAs

Syndication also has disadvantages and can lead to costs that may outweigh the benefits and make syndication unattractive. Many of these costs are personal, and their level, as well as the importance attached to them, varies depending on the personality of the BA. Syndication can lead to severe agency conflicts within the investment syndicate and thereby create transaction costs. Freeriding behavior can occur and can lead to costs to monitor or sanction opportunistic behavior (De Clerq and Dimov, 2008). Such freeriding, coordination, and monitoring costs increase with syndication size (Manigart et al., 2006). However, even with goal alignment between the syndication partners and without agency conflicts, there is often a high need for coordination between the syndication partners (Fried and Hisrich, 1995). Wright and Lockett (2003), for example, argue that even with familiar syndicate partners, there is a high likelihood of complications, difficult negotiations, and delays in decision-making.

In the next section, we shall argue that the personality of the BA influences their investment decisions (i.e., investing via syndication) because personality determines a general, coherent pattern in a person’s decision-making across different contexts and situations, including investment decisions. We shall argue that in the specific case of syndication personality influences (1) the level of benefits and costs associated with syndication and (2) the importance attached to these benefits and costs by the respective individual BA. While the first aspect refers to the objective level of costs and benefits, the second aspect refers to the subjective weight attached to these benefits and costs.

3.3 Theory and hypotheses

3.3.1 A personality perspective on syndication

Personality can be defined as the sum and characteristic structure of a person's personality characteristics (e.g., traits), reflecting his or her characteristic patterns of thinking, feeling, and behaving across different situations (John et al., 2008; McCrae and Costa, 2008). The relatively stable personality traits can be understood as an enduring core of a person's personality, guiding and directing his or her life in certain directions throughout the life course. Research has indeed established this "power of personality", in that traits are remarkably accurate predictors of all sorts of important life outcomes (e.g., happiness, physical and psychological health, and quality of relationships with peers, family, and romantic others, as well as occupational choice, satisfaction, and performance), even when controlling for socioeconomic status and cognitive ability (Ozer and Benet-Martínez, 2005; Roberts et al., 2007). Researchers aiming to explain human behavior and underlying decision-making processes have thus developed a strong interest in the impact that personality traits have.

There is also considerable interest in personality traits in traditionally non-psychological scientific disciplines such as finance (Barber and Odean, 2001; Corter and Chen, 2006; Mayfield et al., 2008). For example, in investor psychology, one tries to understand the effect of personality traits on different forms of investment behavior (e.g., Mayfield et al., 2008; Merkle, 2017). This research demonstrates that investment decisions often cannot be fully explained through economic models based on pure rationality (Kahneman and Riepe, 1998). Inter-individual differences in preferences, attitudes, expectations, and perceptions also play a role, and personality traits shape these psychological processes in a characteristic way, thereby affecting and guiding investment decisions (John et al., 2008). Research found, for example, that expected gains and losses are influenced by personality traits (Boyce et al., 2016). Other research indicates that personality traits shape the perceptions of the potential benefits and costs associated with investments (Mitteness et al., 2012). While such research on the influence of personality on investment decisions has gained momentum in the finance literature in recent years, personality itself has not been accounted for regarding syndication decisions (e.g., BA syndication).

3.3.2 Hypotheses: BA personality (Big Five) and syndication

Many personality researchers agree that the best and, at the same time a highly parsimonious model to capture personality traits is the so-called five-factor model, also known as the Big Five traits (McCrae and Costa, 2008). The Big Five traits are openness to new experience, extraversion, conscientiousness, agreeableness, and neuroticism. The five-factor model is the predominating and most-researched personality model in psychological science (Barrick and Mount, 1991; John et al., 2008; Obschonka et al., 2013). In the following, we formulate hypotheses on how the Big Five relate to BA syndication. The hypotheses are based on three core assumptions. First, personality influences the respective levels of costs and benefits of syndication. Second, personality traits shape the individual perceptions and expectations as well as the importance attached to these benefits and costs of syndication. Third, as people are motivated to have a certain coherence in their personality and in their decision-making and behavioral patterns across different contexts and situations (Cervone and Shoda, 1999), BAs make investment decisions (e.g., syndication vs. investing alone) that fit their personality trait structure to achieve and maintain such personality coherence as a general intra-psychological motive.

Openness to experience

Openness to experience is a Big Five trait that summarizes an individual's tendency to favor creativity and new situations. People high in this trait are open-minded and often interested in arts and new technologies. Additionally, they generally favor variety and diversity and possess intellectual curiosity (LePine and Van Dyne, 2001). Hence, people high in openness often score high in creativity and divergent thinking tests (Batey and Furnham, 2006), indicating highly developed cognitive abilities and skills. Finally, they are more open to stereotype-disconfirming information than other individuals, which facilitates the correction of individual prejudices and stereotypes (Flynn, 2005). People scoring low in this trait, in turn, favor conventions and traditions. They are less attracted by diversity and variety.

Syndication involves cooperation that represents more diversity (the investor team compared to investing alone) and incurs a higher need for coordination between the syndication partners than investing alone. Cooperation can lead to multiple complications, such as difficult negotiations and delays in decision-making. We argue that the coordination within the syndicate becomes easier and less costly with syndicate partners who are open to divergent opinions, attitudes, and behaviors. Also, BAs who are high in openness might not perceive these coordination costs as important or painful because they see the necessity to coordinate with syndicate partners also as an opportunity to gain new experiences by learning from others. In other words, they might be more open to and attracted by diversity in an investor team. They might also have better cognitive skills to cope with and utilize this diversity. Therefore, we expect BAs who are high in openness to engage in syndication more often and hypothesize the following:

> ***Hypothesis 1****: BAs with high levels of openness are more likely to syndicate their investments than are BAs with low levels of openness.*

Extraversion

Extraversion describes an individual's tendency to favor an outgoing, talkative, and energetic style in one's social interactions (e.g., Furnham, 1981). The most important implication of high extraversion is usually seen in an extravert's tendency to prefer and enjoy (active) engagement in social groups (compared to doing things alone). Research shows that extraverts are generally enthusiastic and active when working in groups because this social setting rewards them via neurobiological mechanisms (Ashton et al., 2002). In other words, individuals high in this trait seek active engagement in groups as they obtain socio-emotional benefit out of it. This interpersonal engagement was validated in a wide range of contexts. Research showed, for example, that university students who are high in extraversion show a stronger preference to work in groups (vs. alone) (Chamorro-Premuzic et al., 2005). Workers who are high in extraversion show more self-efficacy for participating in self-managed workgroups than workers low in this trait (Thoms et al., 1996).

Syndication requires BAs to cooperate with other investors, which is generally associated with some costs, such as a need for coordination between the syndication partners. We argue that this disadvantage and cost of syndication will be perceived as less painful by BAs high in extraversion. Given that the central characteristic of extraversion is the preference for actively engaging in social interactions and groups (Depue and Collins, 1999), compared to doing things alone, it seems plausible to assume that extraverted BAs will show a stronger tendency for syndication than introverted BAs. Similar to BAs high in openness, they might even attach a positive value to the need for coordination. Yet, it is the social aspect of coordination and not the learning aspect that matters for them. We hypothesize:

Hypothesis 2*: BAs with high levels of extraversion are more likely to syndicate their investments than are BAs with low levels of extraversion.*

Conscientiousness

Conscientiousness is a Big Five trait that mirrors efficient self-regulation and the capacity to organize and manage one's projects alone. This trait has thus been established as the central trait in research on individual academic and work performance (Barrick and Mount, 1991; Higgins et al., 2007). People scoring high in conscientiousness show high levels of self-discipline and achievement-orientation. Thus, these people prefer to work in settings that require high levels of independence and self-regulation and self-discipline such as entrepreneurship (Brandstätter, 2011). People high in this trait also show less risky and more healthy behaviors, which explain why they show better health and longevity than people low in this trait (Bogg and Roberts, 2004). People who score low in conscientiousness are more laid back, less self-organized, more chaotic, and less driven by individual success. They often exhibit procrastination (Watson, 2001) and are perceived as relatively low in professionalism by their peers (Finn et al., 2009). As "they lack the tenacity to persevere in most situations", they received intensified attention in intervention research aiming at promoting work-related performance and the effective training of work skills (Cheramie and Simmering, 2010, p. 45).

Since people scoring high in this trait tend to get things done alone in a structured and efficient manner, we expect BAs scoring high in this trait to prefer investing alone and not in syndication. We argue that the costs incurred by syndication are higher for BAs high in conscientiousness. Such costs comprise agency and coordination costs. To avoid opportunistic and freeriding behavior within the syndicate, monitoring efforts are necessary. Moreover, to establish goal alignment between the syndicate partners, extensive coordination between the syndicate partners is needed. BAs high in conscientiousness will invest more in monitoring and coordination efforts and will perceive such efforts as more painful. After all, they strive for a well-planned, efficient, and highly-structured investment process which is more difficult to achieve when investing with others. In turn, BAs with low scores in conscientiousness might prefer to invest in groups as compensation for their low self-regulation and self-discipline. They benefit strongly from syndication as they are unlikely to carry out careful due diligence themselves. Finally, BAs high in conscientiousness might show a stronger self-oriented perfectionism tendency than might other BAs (Hill et al., 1997), so they could prefer to invest alone because they are more in control of this particular project and their participation and achievements in this project. We thus hypothesize the following:

> ***Hypothesis 3****: BAs with high levels of conscientiousness are less likely to syndicate their investments than are BAs with low levels of conscientiousness.*

Agreeableness

Agreeableness is the Big Five trait that summarizes an individual's tendency towards harmony and altruism, for example, in social interactions. People scoring high in this trait show more trust, compliance, and modesty. People who are not agreeable, in turn, focus on competition and show rather selfish behavior with a tendency to manipulate others (Jakobwitz and Egan, 2006). High scores in agreeableness are associated with a high need for affiliation because these people show cooperative values and a preference for harmonious interpersonal relationships (Zhao and Seibert, 2006). People who are low in agreeableness are typically driven by higher self-interest and are also more likely to manipulate others for their own advantage. They can drive hard bargains due to their non-conformist attitude.

Syndication involves the need for cooperative decision-making and negotiations leading to coordination and negotiation efforts. We argue that the costs associated with these efforts depend on the level of agreeableness of the syndication partners. BAs high in agreeableness strive for harmony in the syndicate and are likely to trust their syndication partners. The likelihood of severe conflicts decreases. This is underlined by the fact that individuals with high levels of agreeableness favor conformist group perspectives (e.g., they tend to show better capabilities of reaching common decisions and prefer to engage in cooperative efforts more often than do individuals with low levels of agreeableness). Moreover, BAs who are high in this trait are likely to show more trust in others (e.g., other investors in a particular project) (Evans and Revelle, 2008), which might make it easier for them to invest via syndication. Therefore, we hypothesize the following:

> ***Hypothesis 4****: BAs with high levels of agreeableness are more likely to syndicate their investments than are BAs with low levels of agreeableness.*

Neuroticism

Finally, neuroticism is the Big Five trait that describes subclinical neurotic tendencies in the sense that people scoring high in this trait are more prone to negative feelings such as fear, guilt, anger, or worry. They tend to cope with stress and risky and uncertain situations less effectively, are moodier, and have a rather negative perspective on the world as such (Barlow et al., 2014). Therefore, people high in neuroticism avoid risks, whereas people low in neuroticism are emotionally stable, self-confident, and remain calm in difficult situations. Research consistently showed, for example, that individuals higher in neuroticism are less likely to engage in activities that involve risks and uncertainty as well as higher levels of stressors (Brandstätter, 2011). Moreover, high levels of this trait are an important risk factor for clinical disorders such as panic disorder, depression, or phobias, so high neuroticism levels can impose high costs for society (Cuijpers et al., 2010).

BAs may often engage in syndication to diminish their investment risks via cooperation (Manigart et al., 2006; Dimov and Milanov, 2010). Hence, BAs high in neuroticism could show low levels of self-confidence and risk-taking as well as an inability to cope with high uncertainty and risks. Therefore, they could tend to engage in cooperative investment behavior such as syndication, which minimizes risks and helps to cope with such risks. It could also help avoid the feeling of being on one’s own when facing risk and uncertainty. Research has shown, for example, that people who are high in neuroticism put a special emphasis on loss aversion in risky decision-making processes (e.g., Lauriola and Levin, 2001). We thus hypothesize the following:

> ***Hypothesis 5****: BAs with high levels of neuroticism are more likely to syndicate their investments than are BAs with low levels of neuroticism.*

3.4 Data and method

3.4.1 Data sources and data set

We draw on Crunchbase (www.crunchbase.com) to identify our sample of BAs. Crunchbase is a public database that provides a comprehensive overview of VC funding and the entities involved, such as BAs, large VC funds, and corporate VC funds. Because of its extensive and recent coverage, Crunchbase is increasingly used to assess questions on new venture financing (e.g., Ter Wal et al., 2016). Importantly, Crunchbase also contains information on investor's private social media channels (e.g., Twitter, Facebook, LinkedIn). We extracted all BA data available in Crunchbase in October 2016 and identified a sample of 2,114 BAs that used Twitter. In addition to their name and Twitter account, we obtained data on their investments from Crunchbase, such as data on the venture and the financing round.

We use novel data to assess our hypotheses. To gain insights on BAs' psychological traits, we analyze each BA's Twitter profile via a computerized language assessment using the Receptiviti API (www.receptiviti.ai). Receptiviti is the commercial variant of Linguistic Inquiry and Word Count (LIWC), which is the established standard software to assess language for psychological purposes (e.g., Pennebaker et al., 2015; Tausczik and Pennebaker, 2010). While language and text analysis have a rich history in the field of psychology, it has seen little use in the field of entrepreneurship. Based on an individual's Twitter profile, Receptiviti provides all measures generated by the academic LIWC application as well as several "composite" psychological measures, such as the Big Five personality traits (Pennebaker et al., 2015). Receptiviti has been used by Obschonka et al. (2017) and Obschonka and Fisch (2018) to contrast the psychological profiles of entrepreneurs, managers, and politicians. These studies also provide further information on the validity and measurements of Receptiviti.

We collect further personal data on the BAs (e.g., gender, age, education). Unfortunately, this information is available from Crunchbase in only a very rudimentary way (e.g., only 25% of the BAs had their year of birth registered in Crunchbase). Therefore, we performed an extensive web search and manually drew on newspaper articles, LinkedIn profiles, CVs on corporate websites, and other online resources to obtain this information if possible. To account for the national culture of the BA, we used Hofstede's cultural dimensions framework (Hofstede, 1980) and retrieved data on national cultural dimensions from Geert Hofstede's website (www.geerthofstede.nl).

Our initial dataset was reduced for multiple reasons. First, and in line with previous research, we focused on first-round investments only because a BA enters an existing syndicate if it is not first-round funding (e.g., De Clerq and Dimov, 2008; Gompers, 1995; Sahlman, 1990). Thus, the decision to syndicate cannot be decided upon by the BA anymore, or at least not to the same extent as in first-round investments. Second, not everything that is broadcasted on Twitter can be analyzed with language analysis software. Hence, Receptiviti uses a cleaning algorithm to exclude phrases that do not reflect an individual's personality, such as links, hashtags, and Retweets (i.e., simply repeating a message of another account). Receptiviti also requires a minimum number of words per person to deliver meaningful results, leading to the exclusion of accounts with a very low number of Tweets. Finally, we had to drop several observations because of missing values. Our final sample is still extensive and consists of 1,348 BAs that participated in 3,234 first-round investments.

3.4.2 Variables used in our main analysis

In addition to our dependent variable (syndication) and our independent variables (Big Five personality traits), we use several control variables that can be grouped into control variables at the level of the venture, BA, and Twitter. All variables are displayed in Table 3.1, with brief descriptions. Table 3.1 also includes variables that are included in sensitivity analyses (Section 3.6) and further exploratory analyses using other outcome variables (Section 3.7).

Dependent variable (syndication)

Consistent with previous research, we captured *syndication* with a dummy variable equal to one if the investment was syndicated, and 0 if not (e.g., De Vries and Block, 2011; Gu and Lu, 2014). This variable is constructed from Crunchbase's data on venture financing.

Independent variables (Big Five)

We used the Big Five personality traits (five-factor model, FFM) to measure BAs' psychological profiles and test our hypotheses. The data were obtained from Reciptiviti. While the algorithms of many Receptiviti measures are proprietary, they have primarily been established using widely used and well-validated psychometric techniques and principles, including various multi-method approaches that combine standard machine learning procedures with self-report, behavioral, and outcome data as well as domain expertise. Due to the varying constructions of the dimensions, they are scaled differently, but most range between -50 (very low score) and +50 (very high score) (Obschonka et al., 2017).

Control variables (venture level)

Multiple characteristics of the financed venture could influence the likelihood of syndication and are therefore controlled for. Data on this set of variables are obtained or constructed from Crunchbase. First, we control for the *amount raised (log.)*, indicating the amount of money (in $) that the venture raised in the respective funding round in which the BA was involved. Because of its skewness, we include the variable in log form. We control for this variable because sharing financial risk is one of the main drivers of syndication. Thus, the greater the amount invested, the higher the likelihood of syndication (e.g., Cumming et al., 2005; De Clerq and Dimov, 2004, 2008). Additionally, Ter Wal et al. (2016) used this variable to control for differing initial startup conditions, such as the founder's social capital and perceived quality of the idea.

The size of the venture correlates with investment risk (Perez-Quiros and Timmermann, 2000). We control for the *venture's number of employees* as a proxy for *venture size*. This variable is obtained from Crunchbase in ordinal form. The smallest category (= 1) refers to ventures with 1 to 10 employees, while the largest category refers to ventures with more than 1,000 employees (= 7).

Following similar reasoning, we control for the *venture's age (log.)* (e.g., Cumming et al., 2010, De Vries and Block, 2011). Older ventures often have a more established business and have proven themselves over a longer time frame without failure, thus reducing investors' uncertainty and making syndication less likely (De Clerq and Dimov, 2008).

Another factor that is crucial for investment decisions are the characteristics of the venture's founding team (e.g., Cumming et al., 2016; Mason and Stark, 2004). For example, a venture with a lone founder might signal a higher investment risk than a venture with a founding team, making syndication more likely. However, on the other hand, lone founder ventures typically grow slower than ventures with a founding team, decreasing resource requirements, and potentially making syndication less likely. We control for the *venture's number of founders*, which we obtained from Crunchbase.

In line with prior syndication research (e.g., Cumming et al., 2010; De Vries and Block, 2011; Meuleman and Wright, 2011; Sorensen and Stuart, 2008), we control for the *location* of the venture by including two dummy variables that capture whether the venture is headquartered in the US, the EU, or elsewhere in the world. The location and regional environment of the venture influence the market, the political uncertainty and, hence, the investment risk, and they create market opportunities. Supporting this finding, Gu and Lu (2014) find a severe impact of the business and political environment on syndication behavior. In our robustness checks, we also include country dummies for each country in our dataset.

Investments in early venture stages generally entail greater uncertainty and should thus make syndication more likely. Hence, and in line with previous research, we control for venture stage (e.g., Cumming et al., 2010; De Clerq and Dimov, 2008; Gu and Lu, 2014; Hopp and Lukas, 2014). We distinguish two stages based on Crunchbase and include a dummy variable that captures whether a venture is in the *seed stage* (= 1) or not (= 0).

Finally, we included a set of *year dummies* capturing the year in which the venture received funding and a set of *industry dummies* referring to the industry in which the venture is active. Previous research indicates that both differences over time and across industries, for example, due to different competitive intensities and growth prospects, can impact the syndication behavior (e.g., De Clerq and Dimov, 2008; Ma et al., 2013; Gu and Lu, 2014; Ter Wal et al., 2016).

Control variables (country level)

Cross-cultural research has established that cultural differences play an important role in explaining cross-country differences in the perceptions and behaviors of entrepreneurial finance investors (e.g., Li and Zahra, 2012). One of the most commonly used measures of (national) culture is Hofstede's cultural dimensions framework (Hofstede, 1980), distinguishing between four different dimensions of culture: power distance, individualism, masculinity, and uncertainty avoidance. Dai and Nahata (2016) show that cultural differences are important in explaining VC syndication, particularly in cross-border investments. Similarly, culture is likely to be an important contextual factor for BA investments and syndication (e.g., Brush et al., 2002; Cumming and Zhang, 2019). For example, BAs in countries with a high uncertainty avoidance might generally have a higher preference to reduce investment risk by syndication. To control for these potential differences in our international sample, we include the cultural dimensions of Hofstede as control variables in our models.

Control variables (BA level)

We also include a set of control variables at the BA level. Previous research in the VC domain has consistently shown that previous experience influences the likelihood of syndication. If investors have already undertaken multiple investments, they are less likely to engage in syndication because their experience reduces the uncertainty that they would otherwise seek to reduce via syndication (e.g., Cumming et al. 2010, 2016; Dimov and Milanov, 2010; Gu and Lu, 2014; Hopp and Lukas, 2014). While previous research has focused on VC funds as institutional investors, we expect that this finding also applies to BAs. We thus control for a BA's number of *previous investments (log.)*, which is calculated based on Crunchbase data.

Additionally, demographic characteristics are likely to influence syndication behavior (e.g., Dimov and Shepherd, 2005; Gompers et al., 2016b). First, we account for the age of the respondent by including a variable that captures the BA's *age* (in years) at the time of the investment decision. Again, previous research has shown that older people tend to be more risk-averse, while a younger age is associated with a higher willingness to take risks (e.g., Hambrick and Mason, 1984). Hence, one could expect that older people are more likely to engage in syndication. We also control for an individual's current location, as syndication behavior might differ across regions. Specifically, we distinguish between BAs located in the US (= 1) and elsewhere (= 0). Then, we control for an individual's gender. For example, previous research has shown that women, in general, are more risk-averse than men, particularly with regard to financial decision making (Jianakoplos and Bernasek, 1998). Therefore, it could be expected that women are more likely to engage in syndication, and thus we include a dummy variable that captures whether an individual is *male* (= 1) or not (= 0). Another important individual characteristic is education. Gompers et al. (2016b) show that education is very important to a VC's investment behavior. While they focus on differences between top schools, we follow Dimov and Shepherd (2005) and measure the BA's field of studies. Dimov and Shepherd (2005) show that there are, for example, huge differences in the investment decisions of individuals with backgrounds in entrepreneurship, the sciences, or the humanities. Hence, we capture whether a

BA has an education in business/economics (*education: business*) with a dummy variable. Additionally, we include a dummy variable that captures whether the BA has a background in Tec/Sci (*education: tec/sci)*, for example, in the fields of computer science, engineering, or chemistry. Finally, we capture whether an individual has a *PhD* (= 1) or not (= 0).

Finally, we include a set of variables to control for the BAs' *ethnicity*. Gompers et al. (2016b) find ethnicity to be an important factor in an individual's syndication decisions. We follow Gompers et al. (2016b) and Kerr and Lincoln (2010) and use a name-based matching algorithm to determine ethnicity. Similar to Gompers et al., (2016b), we account for the region of the BA's undergraduate academic institution or school as well as other information available in Crunchbase to determine their most likely ethnicity. This approach results in six non-overlapping ethnic groups: African American, East Asian, Hispanic, Indian, Middle Eastern, and all others (mostly White).

Control variables (Twitter level)

Finally, we control for a set of variables at the Twitter level because we want to rule out confounding effects due to different usages of Twitter by the BAs. While novel in the field of entrepreneurial finance, Twitter is used frequently as a data source in psychology (Qiu et al., 2012) and the computer sciences. In the latter, it is used, among other purposes, to study the diffusion of information and communication in networks (e.g., Bakshy et al., 2011; Krishnamurthy et al., 2008; Kwak et al., 2010). This research has consistently used three key variables to characterize Twitter usage that we thus include as control variables: The number of *followers* (i.e., people who subscribe to the account and receive the messages), the number of *followees* (i.e., people whom the users follow themselves and whose messages they receive), and the number of *tweets* (i.e., the messages a user posts on Twitter). These variables were collected directly via the Twitter API at the same time that we collected the Crunchbase data (October 2016). Because of their skewness, we include the Twitter-based variables in log form.

3.5 Main results

3.5.1 Descriptive statistics

Descriptive statistics for the full sample are displayed in Table 3.2, along with the correlations and variance inflation factors. In total, approximately 95% (3,073 of 3,234) of the investments in our sample were syndicated, indicating a strong preference for syndication among BAs. With regard to the Big Five personality traits, the mean values indicate relatively high values in extraversion and neuroticism and comparatively low values in agreeableness. Notice, however, that the values drawn from Receptivity are scaled differently and should therefore not be compared directly.

With regard to the funded ventures, Table 3.2 shows that the average venture in our sample raised approximately 1.3 $m (log. = 14.07) during its first round of investment. With 108 $m "Impossible Foods" is the venture in our dataset that raised the most money. The average venture size is 2.2, which corresponds to the group of ventures with 51 to 100 employees. The average number of founders per venture is 2.3 and the ventures were on average 5.6 years old (log. = 1.73), as of 2017. Unsurprisingly, 93% of the ventures were headquartered in the US (Europe: 3%; rest of the world: 4%) and approximately 64% of the ventures in our sample were in a seed stage.

With regard to the cultural dimensions, which could theoretically scale up to 120, the average power distance (40.6) and uncertainty avoidance (46.6) are rather low, while the value of masculinity is moderate (61.7). The value of individualism is high (89.4). These values are biased towards the US because of the dominance of US investors in our sample.

The average BA has a track record of 4.2 previous investments (log. = 1.44) and is 44 (log. = 3.78) years old. The oldest investor in our dataset was born in 1928, while the youngest investor was born in 1996. Note that these mean values are slightly skewed because BAs that made multiple investments appear multiple times in our dataset.[6] 95% of the BAs are male. Our sample is very US-centric. 92.5% of the observations refer to BAs that are located in the US. The second-largest groups are the United Kingdom (2.1%) and India (1.0%). The remaining 4.4% of the observations are from other countries around the world. With regard to their educational background, 49% of the BAs have a background in business administration or economics, 40% have a background in a technical or scientific field, such as engineering, chemistry, or computer sciences, and 17% have a PhD. Notice that education classifications are not exclusive. With regard to their ethnicity, 1% of the BAs are African American, 4% are East Asian, 3% are Hispanic, 6% are Indian, 5% Middle Eastern, and approximately 81% are of White ethnicity. These values are roughly comparable to the ratios reported by Gompers et al. (2016b).

With regard to Twitter measures, on average, the BAs posted 2,566 Tweets (log. = 7.85), have 10,199 followers (log. = 9.23) and 572 followees (log. = 6.35). Often, the ratio of followers and followees is thus used to measure the influence of Twitter users (e.g., Bakshy et al., 2011; Kwak et al., 2010). Users with a high ratio of followers/followees can be characterized as broadcasters of tweets, while users with a very low ratio have been characterized as miscreants (e.g., spammers or stalkers) or evangelists, who contact everyone they can, and hope that some will follow them (Krishnamurthy et al., 2008).

[6] When correcting for this distortion, the business angels are 43 years old on average, 91% are located in the US, 95% are male, 48% have a background in business, 42% have a background in tec/sci, 11% hold a PhD, 1% are African American, 5% are East Asian, 3% are Hispanic, 7% are Indian, and 6% are of Middle Eastern ethnicity.

Table 3.1: Variables and their descriptions

This table summarizes all variables, their descriptions, and the data source for each variable.

Variable name	Description	Data source
Dependent Variable		
Syndication	Dummy variable that captures whether the investment was syndicated (= 1) or not (= 0).	Crunchbase
Independent variables: Big Five		
Openness	Degree to which a person is open to new ideas and new experiences.	Receptiviti (Twitter)
Extraversion	Degree to which a person feels energized and uplifted when interacting with others.	Receptiviti (Twitter)
Conscientiousness	Degree to which a person is reliable.	Receptiviti (Twitter)
Agreeableness	Degree to which a person is inclined to please others.	Receptiviti (Twitter)
Neuroticism	Degree to which a person expresses strong negative emotions.	Receptiviti (Twitter)
Control variables: Venture level		
Amount raised (log.)	The amount that was raised in the venture’s funding (in $ and in logged form).	Crunchbase
Venture: Age (log.)	Age (in years) of the venture.	Crunchbase
Venture: No. of emp.	Number of employees of the venture (in seven size classes, from 1–10 to 1000+).	Crunchbase
Venture: No. of founders	Number of founders of the venture.	Crunchbase
Venture: Location US	Dummy variable that captures whether the venture is located in the US (= 1) or not (= 0).	Crunchbase
Venture: Location EU	Dummy variable that captures whether the venture is located in the US (= 1) or not (= 0).	Crunchbase
Round: Seed-stage	Dummy variable that captures whether the venture was in a seed-stage (= 1) or not (= 0).	Crunchbase
Year dummies	Dummy for the year in which the venture received its first funding (8 dummies).	Crunchbase
Industry dummies	Dummy for the industry in which the venture is mainly active (21 dummies).	Crunchbase
Control variables: Country level		
Hofstede: Power distance	Degree to which the less powerful members of a society accept and expect that power is distributed unequally.	www.geerthofstede.nl
Hofstede: Individualism	Individuals are expected to take care of only themselves and their immediate families.	www.geerthofstede.nl
Hofstede: Masculinity	Preference in society for achievement, heroism, assertiveness, and material rewards for success.	www.geerthofstede.nl
Hofstede: Uncertainty avoidance	Degree to which the members of a society feel uncomfortable with uncertainty and ambiguity.	www.geerthofstede.nl
Control variables: Investor level		
Previous investments (log.)	The number of previous investments the BA had conducted prior to the current investment.	Crunchbase
BA: Age (log.)	Age (in years) of the BA.	Crunchbase, CVs, …
BA: Location US	Dummy variable that captures whether the BA is from the US (= 1) or not (= 0).	Crunchbase, CVs, …
Male	Dummy variable that captures whether the BA is male (= 1) or not (= 0).	Crunchbase, CVs, …
Education: Business	BA has an educational background business or economics (= 1) or not (= 0).	Crunchbase, CVs, …
Education: Tec/Science	BA has an educational background in the field of Tec/Sci (= 1) or not (= 0).	Crunchbase, CVs, …
Education: PhD	Dummy variable that captures whether the BA has a PhD (= 1) or not (= 0).	Crunchbase, CVs, …
Ethnicity: African American	Dummy variable that captures whether the BA is of African American ethnicity (= 1) or not (= 0).	Crunchbase, CVs, …
Ethnicity: East Asian	Dummy variable that captures whether the BA is of East Asian ethnicity (= 1) or not (= 0).	Crunchbase, CVs, …
Ethnicity: Hispanic	Dummy variable that captures whether the BA is of Hispanic ethnicity (= 1) or not (= 0).	Crunchbase, CVs, …
Ethnicity: Indian	Dummy variable that captures whether the BA is of Indian ethnicity (= 1) or not (= 0).	Crunchbase, CVs, …
Ethnicity: Middle Eastern	Dummy variable that captures whether the BA is of Middle Eastern ethnicity (= 1) or not (= 0).	Crunchbase, CVs, …
Control variables: Twitter level		
Tweets (log.)	The number of messages (“Tweets”) a BA has sent on Twitter (in logged form).	Twitter
Followers (log.)	The number of accounts that follow a BA (“Followers”) on Twitter (in logged form).	Twitter
Follows (log.)	The number of accounts that a BA follows (“Followees”) on Twitter (in logged form).	Twitter
Variables used in sensitivity analyses and further analyses		
Syndicate size	Number of investors involved in the syndicate in four classes: 1, 2–5, 6–10, and 10+.	Crunchbase
Lead investor	Dummy variable that captures whether the BA was a lead investor (= 1) or not (= 0).	Crunchbase
Syndicate composition	Captures whether the BA (1) invests alone, (2) with other BAs, (3) with VCs, or (4) with multiple/other investor types.	Crunchbase
Follow-up round	Dummy variable that captures whether the venture received a follow-up round of financing (= 1) or not (= 0).	Crunchbase
Successful venture exit	Dummy variable that captures whether the venture was acquired or went public (= 1) or not (= 0).	Crunchbase
Investor exit	Dummy variable that captures whether the BA eventual exited from the venture (= 1) or not (= 0).	Crunchbase
Venture survival	Dummy variable that captures whether the venture is active (= 1) or closed (= 0).	Crunchbase

Table 3.2: Descriptive statistics, correlations, and variance inflation factors

This table presents the means, standard deviations, minimum values, and maximum values for the variables used in our main analyses. This table also displays the pairwise correlations between the variables (values below -0.05 or above 0.05 are significant at the level of 5%). The last column displays the variance inflation factors (VIF), which are estimated based on Model 6 in Table 3.4. The total number of observations is 3,234 investments from 1,348 BAs. All variables are defined in Table 3.1. The reference category for the venture's location dummies is "Venture: Location rest of the world". The reference category for the education dummies is "Education: Other/unknown". The reference category for ethnicity dummies is "Ethnicity: Other".

	AM	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	VIF
Dependent Variable																																				
(1) Syndication	0.95	0.22	0.00	1.00																																1.14
IV: Big Five																																				
(2) Openness	2.21	1.04	-1.57	5.56	-0.02																															1.53
(3) Extraversion	3.66	1.38	-0.23	7.44	0.04	-0.26																														2.36
(4) Conscientiousness	1.72	1.30	-1.58	5.72	-0.06	0.33	0.35																													2.21
(5) Agreeableness	0.39	2.17	-7.12	4.68	-0.02	-0.09	0.65	0.47																												2.20
(6) Neuroticism	3.92	2.15	-3.08	11.56	0.00	0.21	-0.57	-0.46	-0.50																											2.02
CV: Venture level																																				
(7) Amount raised (log.)	14.07	1.23	6.91	18.50	0.28	0.06	0.05	0.03	0.02	0.00																										1.50
(8) Venture: Age (log.)	1.73	0.41	0.00	3.30	-0.02	0.02	-0.03	0.02	-0.03	0.02	-0.02																									2.77
(9) Venture: No. of emp.	2.23	1.30	1.00	7.00	0.05	0.02	0.01	0.03	0.01	0.02	0.27	0.23																								1.28
(10) Venture: No. of founders	2.26	1.07	1.00	9.00	0.07	0.02	-0.01	0.02	0.00	0.00	0.02	-0.07	0.08																							1.05
(11) Venture: Location US	0.93	0.25	0.00	1.00	0.03	-0.01	-0.01	-0.02	-0.02	0.02	0.08	0.05	0.00	-0.02																						2.01
(12) Venture: Location EU	0.03	0.17	0.00	1.00	-0.03	0.00	0.01	0.00	0.02	-0.01	-0.07	-0.01	0.02	0.02	-0.65																					1.91
(13) Round: Seed-stage	0.64	0.48	0.00	1.00	0.00	-0.04	-0.03	-0.06	-0.03	0.03	-0.25	-0.32	-0.22	0.00	0.00	-0.01																				1.33
CV: Country level																																				
(14) Hofstede: PD	40.62	5.73	13.00	93.00	-0.05	0.02	0.07	0.04	0.08	-0.07	-0.08	-0.09	-0.01	0.02	-0.14	-0.02	0.00																			2.87
(15) Hofstede: Individualism	89.35	7.91	20.00	91.00	0.05	-0.02	-0.02	-0.02	-0.07	0.05	0.10	0.08	0.01	-0.02	0.24	-0.11	0.00	-0.75																		5.77
(16) Hofstede: Masculinity	61.65	3.87	5.00	95.00	0.08	-0.03	0.01	-0.02	-0.03	0.03	0.07	0.04	0.03	-0.01	0.13	-0.09	0.03	-0.28	0.40																	1.22
(17) Hofstede: UA	46.59	6.19	23.00	99.00	-0.05	0.05	-0.04	0.05	0.02	-0.02	-0.06	-0.01	-0.01	0.03	-0.04	0.07	0.02	0.43	-0.53	-0.24																1.55
CV: Investor level																																				
(18) Previous inv. (log.)	1.44	1.39	0.00	5.28	0.12	0.06	-0.10	0.00	-0.15	0.18	0.20	-0.16	-0.02	0.04	-0.07	0.05	0.04	-0.04	0.09	0.04	-0.08															1.57
(19) BA: Age (log.)	3.78	0.21	3.04	4.47	-0.02	0.08	-0.01	0.23	0.03	-0.07	0.08	0.21	0.03	-0.03	0.02	-0.01	-0.13	-0.07	0.07	0.04	-0.04	0.09														1.32
(20) BA: Residence US	0.93	0.26	0.00	1.00	0.06	-0.02	-0.04	-0.01	-0.06	0.03	0.09	0.07	0.03	-0.02	0.34	-0.26	-0.02	-0.38	0.73	0.31	-0.34	0.11	0.07													2.82
(21) Male	0.95	0.21	0.00	1.00	-0.02	0.09	-0.12	0.03	-0.08	0.02	-0.02	0.00	0.01	0.01	0.01	-0.02	0.02	0.03	-0.04	-0.03	0.04	0.01	-0.10	-0.03												1.09
(22) Education: Business	0.49	0.50	0.00	1.00	-0.02	0.02	0.08	0.13	0.17	-0.04	-0.02	0.03	0.02	-0.01	-0.05	0.05	0.00	0.04	-0.04	-0.02	0.05	0.01	0.09	-0.01	0.02											1.21
(23) Education: Tec/Sci	0.40	0.49	0.00	1.00	0.02	0.04	-0.14	-0.05	-0.04	0.00	-0.04	-0.05	-0.03	0.05	-0.04	0.00	0.04	0.10	-0.06	-0.03	0.02	-0.04	0.00	-0.03	0.10	-0.22										1.34
(24) Education: PhD	0.17	0.38	0.00	1.00	0.04	-0.01	0.03	-0.02	-0.05	0.06	0.05	0.04	0.02	-0.02	0.07	-0.05	-0.02	-0.02	0.05	0.03	-0.03	0.18	0.10	0.07	-0.02	-0.14	-0.22									1.23
(25) Ethnicity: Afr. American	0.01	0.11	0.00	1.00	-0.07	0.01	-0.01	-0.02	0.01	-0.01	-0.04	-0.03	-0.01	0.00	0.03	-0.02	0.03	0.01	0.00	0.01	-0.01	-0.04	-0.01	0.02	0.01	-0.08	-0.06	-0.05								1.09
(26) Ethnicity: East Asian	0.04	0.21	0.00	1.00	0.03	-0.01	-0.05	0.01	-0.01	-0.01	0.01	-0.06	0.00	-0.01	0.02	-0.03	0.04	-0.01	0.02	0.06	0.01	-0.05	-0.15	0.04	-0.04	-0.01	0.10	0.02	-0.02							1.10
(27) Ethnicity: Hispanic	0.03	0.16	0.00	1.00	0.00	-0.05	0.08	-0.07	0.08	-0.04	0.02	-0.01	-0.01	0.00	0.02	-0.03	0.01	0.04	-0.06	-0.01	0.04	-0.01	-0.08	0.00	0.03	0.05	-0.03	-0.05	-0.02	-0.04						1.08
(28) Ethnicity: Indian	0.06	0.25	0.00	1.00	0.01	-0.03	0.09	-0.01	0.12	-0.07	-0.03	-0.07	0.02	0.02	-0.10	-0.02	0.04	0.22	-0.17	-0.03	-0.08	-0.08	-0.09	-0.11	0.02	0.02	0.14	-0.03	-0.03	-0.06	-0.04					1.20
(29) Ethnicity: Middle Eastern	0.05	0.22	0.00	1.00	0.01	0.12	-0.04	0.06	-0.01	0.07	-0.04	0.01	-0.01	0.01	0.01	-0.03	0.01	0.03	-0.11	-0.05	0.09	-0.03	-0.02	-0.03	0.04	0.02	0.12	-0.03	-0.03	-0.05	-0.04	-0.06				1.11
CV: Twitter level																																				
(30) Tweets (log.)	7.85	1.74	3.18	11.86	0.06	-0.05	-0.19	-0.34	-0.36	0.30	0.01	-0.02	0.00	0.00	-0.03	0.00	0.06	-0.03	-0.01	0.02	-0.03	0.26	-0.12	-0.03	-0.04	-0.11	-0.11	0.18	0.05	0.02	0.01	-0.06	0.00			2.81
(31) Followers (log.)	9.23	2.34	2.30	18.20	0.07	-0.01	-0.04	-0.12	-0.18	0.20	0.20	0.02	0.09	0.03	-0.02	-0.02	-0.03	-0.01	0.02	0.02	-0.06	0.47	0.05	0.04	-0.06	-0.08	-0.16	0.18	0.12	-0.03	0.05	-0.09	0.01	0.61		2.26
(32) Follows (log.)	6.35	1.40	1.61	16.57	0.02	-0.09	-0.03	-0.15	-0.17	0.05	-0.05	-0.02	-0.04	-0.01	-0.02	-0.03	0.06	-0.06	0.04	0.03	-0.09	0.11	-0.02	-0.01	-0.09	-0.10	-0.04	0.02	-0.01	0.01	0.01	-0.04	-0.03	0.61	0.35	1.75

3.5.2 Univariate analysis

To gain a first overview of potential differences between investments that were syndicated and investments that were not syndicated, we perform a univariate t-test to assess differences in the mean values between the two groups (Table 3.3). In total, 161 investments were not syndicated, while 3,073 investments were syndicated. With regard to the Big Five personality traits, investments that were syndicated are characterized by significantly higher values of extraversion ($p < 0.05$) and significantly lower values of conscientiousness ($p < 0.01$). These differences lend initial support for Hypothesis 2 and Hypothesis 3. However, we find no differences with regard to the remaining personality traits.

With regard to the control variables, Table 3.3 also reveals several differences. For example, syndication seems to be more likely for investments in which the target venture raised more money, has more employees and founders, is younger, and is US-based ($p < 0.05$). In contrast, syndication is less likely for ventures based in Europe ($p < 0.05$). With regard to Hofstede's cultural dimensions, several highly significant differences emerge. The syndication of ventures seems to be more common in countries with a lower power distance and uncertainty avoidance, while it is more common in countries with higher values in individualism and masculinity ($p < 0.01$). With regard to the control variables at the BA level, the results show that a higher number of previous investments can be associated with a higher likelihood of syndication ($p < 0.01$). Additionally, several demographic characteristics differ between the two groups: Syndication seems to be significantly more common among BAs who are younger, US-based, or have a PhD. With regard to ethnicity, investors of African American ethnicity tend to engage less in syndication, while investors of East Asian ethnicity seem to engage in syndication more often. Finally, Table 3.3 indicates that a higher number of Tweets and Followers correlates to a higher likelihood of syndication.

Table 3.3: Univariate analysis

This table displays the mean and standard deviation of each variable for the subgroup of investments without syndication and the subgroup of investments with syndication. The final column displays the difference in the mean values as well as a t-test for the equality of the mean values. The total number of observations is 3,234 investments from 1,348 BAs. All variables are defined in Table 3.1. Significance levels are denoted by asterisks, *** 1%, ** 5%, and * 10% (p -values are two-tailed).

	Syndication = 0 (N = 161)		Syndication = 1 (N = 3,073)		t-test
Variables	*Mean*	*SD*	*Mean*	*SD*	**(0) vs. (1)**
IV: Big Five					
Openness	2.313	0.978	2.210	1.047	0.104
Extraversion	3.421	1.342	3.678	1.385	-0.256**
Conscientiousness	2.045	1.284	1.699	1.302	0.346***
Agreeableness	0.564	1.978	0.382	2.176	0.182
Neuroticism	3.899	2.452	3.917	2.138	-0.019
CV: Venture level					
Amount raised (log.)	12.581	1.667	14.145	1.146	-1.564***
Venture: Age (log.)	1.770	0.465	1.731	0.0411	0.039
Venture: No. of employees	1.926	1.212	2.242	1.302	-0.316***
Venture: No. of founders	1.926	1.159	2.281	1.067	-0.355***
Venture: Location US	0.894	0.308	0.934	0.248	-0.040**
Venture: Location EU	0.056	0.230	0.029	0.167	0.027**
Round: Seed-stage	0.627	0.627	0.636	0.481	-0.008
CV: Country level					
Hofstede: Power distance	41.851	10.781	40.560	5.333	1.291***
Hofstede: Individualism	87.460	11.729	89.450	7.652	-1.991***
Hofstede: Masculinity	60.379	8.007	61.722	3.507	-1.343***
Hofstede: Uncertainty avoidance	47.994	11.159	46.519	5.808	1.474***
CV: Investor level					
Previous inv. (log.)	0.699	0.699	1.483	1.394	-0.784***
BA: Age (log.)	3.801	3.801	3.779	0.205	0.022
BA: Residence US	0.857	0.857	0.929	0.257	-0.072***
Male	0.969	0.969	0.954	0.209	0.015
Education: Business	0.534	0.534	0.486	0.500	0.048
Education: Tec/Sci	0.354	0.354	0.404	0.491	-0.050
Education: PhD	0.106	0.106	0.174	0.379	-0.069**
Ethnicity: African American	0.044	0.043	0.010	0.098	0.034***
Ethnicity: East Asian	0.019	0.019	0.046	0.210	-0.028*
Ethnicity: Hispanic	0.025	0.025	0.027	0.161	-0.002
Ethnicity: Indian	0.056	0.056	0.065	0.247	-0.009
Ethnicity: Middle Eastern	0.044	0.043	0.054	0.225	-0.010
Ethnicity: White	0.814	0.391	0.799	0.401	0.015
CV: Twitter level					
Tweets (log.)	7.420	7.420	7.877	1.740	-0.456***
Followers (log.)	8.535	8.534	9.264	2.322	-0.730***
Follows (log.)	6.251	6.251	6.355	1.398	-0.103

3.5.3 Logistic regression predicting BA syndication

Since our dependent variable is binary, we use logistic regression to analyze the likelihood of syndication and its determinants. Our unit of analysis is the investment. Hence, BAs occur as multiple observations if they performed more than one investment. To account for potential bias in our estimations, we cluster the standard errors at the BA level. In total, our analysis comprises 3,234 first-round investments by 1,348 BAs. The results are displayed in Table 3.4. Our independent variables are entered stepwise in Models 1 to 5 and jointly in Model 6. We do this to assess a potential bias of multicollinearity, even though the low correlations and variance inflation factors displayed in Table 3.2 indicate that there should be no problems due to multicollinearity. Model 6 also includes the odds ratios and the marginal effects when keeping all other variables at their means to better assess the economic significance of our results.

Hypothesis 1 suggests a positive effect of openness on the likelihood of syndication. While we find a negative effect in Model 1, this effect vanishes when the independent variables are entered jointly in Model 6. Hence, the finding is not robust. Conservatively speaking, we find no support for Hypothesis 1. Hypothesis 2 suggests a positive relationship between extraversion and syndication. As shown in Models 2 and 6, we find a highly significant and positive effect ($p < 0.01$), indicating that individuals with higher values in extraversion tend to engage in syndication more often. The odds ratio of 1.39 indicates that an increase in extraversion by one unit increases the odds of syndication by 39%. The marginal effect of 0.005 indicates that a one-unit increase in extraversion increases the probability of syndication by 0.5%. Finally, Hypothesis 3 posits a negative relationship between conscientiousness and syndication. Again, our results support this hypothesis by showing a highly significant negative effect ($p < 0.01$). The odds ratio of 0.73 indicates that a one-unit increase in conscientiousness decreases the odds of syndication by 27%, while the marginal effect indicates that the overall probability of syndication decreases by 0.5%. We find no support for Hypothesis 4 or 5.

Multiple control variables have a significant effect on syndication. Based on Model 6, syndication is more common for ventures that raised more money. This is in line with previous research indicating that sharing the financial risk, which is higher if the investment is higher, is one of the main drivers of syndication (e.g., Cumming et al., 2005; De Clerq and Dimov, 2004, 2008). Additionally, we find that syndication is more common among ventures with a higher number of founders and among ventures in the seed stage. Interestingly, we also find that higher levels of country-level power distance and individualism decrease the likelihood of syndication, while higher values of masculinity increase the likelihood of syndication.[7] With regard to the investor level, we find that a higher number of previous investments increases the likelihood of syndication, as does a younger age and an educational background in a field of science or technology. Ethnicity does not influence syndication significantly.

[7] To ensure the robustness of our results, we also estimated the same model with country dummies (not reported). The main results remain unchanged and can be obtained from the corresponding author.

3.6 Sensitivity analyses

We perform several sensitivity analyses to investigate the robustness of our main findings. These sensitivity analyses comprise changes in estimation techniques, changes to our sample, changes in the dependent variables, and a dedicated assessment of a potential endogeneity bias. To keep the manuscript more concise, we included the respective tables in the Appendix.

3.6.1 Penalized likelihood estimation to account for rare events

In total, 95% of the investments in our sample were syndicated. Hence, non-syndicated investments are comparatively rare. Logistic regression suffers from estimation problems in the case of rare events (i.e., one group of observations is extremely rare). This is because the maximum likelihood estimation used in logistic regressions suffers from a small-sample bias, with the degree of the bias depending on the number of rare observations. There are several methods to account for potential estimation problems with rare events, which we include as robustness checks in this study. The common solution to this problem is the so-called "Firth method", which uses a penalized likelihood estimation to reduce the small-sample bias and produces finite, consistent estimates of regression parameters (King and Zeng, 2001).

We perform a penalized likelihood estimation using the Firth method as our first sensitivity analysis. The results are displayed in the Appendix. Model 1 of Table 3.A1 shows that there are no severe differences from the standard logistic regression. Both the effects of extraversion and conscientiousness on the likelihood of syndication remain highly significant ($p < 0.01$). Note, however, that the Firth method does not allow for clustered standard errors.

Table 3.4: Main analysis: logistic regression on the determinants of syndication

This table shows the results of our main analysis. We perform a logistic regression with the dependent variable syndication (dummy). All variables are defined in Table 3.1. Logits are reported with robust standard errors (SE) clustered by BAs in parentheses. The reference category for the venture's location dummies is "Venture: Location rest of the world". The reference category for the education dummies is "Education: Other/unknown". The reference category for ethnicity dummies is "Ethnicity: Other". Significance levels are denoted by asterisks, *** 1%, ** 5%, and * 10% (p -values are two-tailed).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6		
Variables	*Logit (SE)*	*Logit SE*	*Logit SE*	*Logit SE*	*Logit SE*	*Logit SE*	*OR*	*ME*
CV: Venture level								
Amount raised (log.)	0.912 (0.082)***	0.905 (0.081)***	0.898 (0.082)***	0.902 (0.081)***	0.903 (0.081)***	0.899 (0.081)***	2.457	0.014
Venture: Age (log.)	0.395 (0.421)	0.416 (0.412)	0.400 (0.425)	0.414 (0.425)	0.434 (0.422)	0.416 (0.413)	1.516	0.007
Venture: No. of employees	0.002 (0.081)	0.004 (0.080)	-0.001 (0.081)	0.000 (0.080)	0.007 (0.081)	0.009 (0.082)	1.009	0.000
Venture: No. of founders	0.422 (0.133)***	0.418 (0.133)***	0.423 (0.132)***	0.419 (0.133)***	0.421 (0.133)***	0.433 (0.136)***	1.543	0.007
Venture: Location US	0.362 (0.477)	0.403 (0.482)	0.335 (0.480)	0.379 (0.480)	0.422 (0.482)	0.386 (0.485)	1.471	0.007
Venture: Location EU	0.195 (0.596)	0.192 (0.590)	0.142 (0.601)	0.206 (0.601)	0.232 (0.601)	0.118 (0.591)	1.125	0.002
Round: Seed-stage	0.408 (0.188)**	0.451 (0.190)**	0.405 (0.186)**	0.419 (0.186)**	0.427 (0.188)**	0.453 (0.194)**	1.573	0.008
CV: Country level								
Hofstede: Power distance	-0.023 (0.020)	-0.030 (0.020)	-0.026 (0.020)	-0.025 (0.020)	-0.024 (0.020)	-0.035 (0.020)*	0.966	-0.001
Hofstede: Individualism	-0.033 (0.021)	-0.037 (0.021)*	-0.034 (0.020)*	-0.033 (0.020)*	-0.032 (0.021)	-0.040 (0.021)*	0.961	-0.001
Hofstede: Masculinity	0.037 (0.017)**	0.037 (0.016)**	0.038 (0.016)**	0.038 (0.016)**	0.039 (0.017)**	0.038 (0.017)**	1.039	0.000
Hofstede: Uncertainty avoidance	-0.010 (0.013)	-0.007 (0.012)	-0.009 (0.012)	-0.011 (0.012)	-0.010 (0.013)	-0.002 (0.012)	0.998	-0.000
CV: Investor level								
Previous inv. (log.)	0.434 (0.087)***	0.465 (0.097)***	0.430 (0.085)***	0.436 (0.089)***	0.450 (0.089)***	0.462 (0.091)***	1.587	0.007
BA: Age (log.)	-1.333 (0.467)***	-1.236 (0.452)***	-1.187 (0.502)**	-1.389 (0.463)***	-1.417 (0.465)***	-0.852 (0.467)*	0.427	-0.013
BA: Residence US	0.632 (0.472)	0.757 (0.482)	0.677 (0.473)	0.650 (0.479)	0.636 (0.482)	0.826 (0.475)*	2.285	0.019
Male	-0.296 (0.528)	-0.202 (0.508)	-0.300 (0.566)	-0.360 (0.516)	-0.377 (0.499)	-0.124 (0.568)	0.883	0.002
Education: Business	-0.087 (0.212)	-0.141 (0.210)	-0.058 (0.218)	-0.095 (0.217)	-0.102 (0.210)	-0.075 (0.211)	0.928	-0.001
Education: Tec/Sci	0.301 (0.218)	0.335 (0.215)	0.327 (0.216)	0.319 (0.216)	0.299 (0.214)	0.334 (0.210)	1.396	0.005
Education: PhD	0.457 (0.318)	0.384 (0.314)	0.443 (0.318)	0.438 (0.312)	0.442 (0.311)	0.321 (0.321)	1.379	0.005
Ethnicity: African American	-0.683 (0.641)	-0.724 (0.610)	-0.691 (0.659)	-0.696 (0.629)	-0.782 (0.615)	-0.757 (0.664)	0.469	-0.017
Ethnicity: East Asian	0.911 (0.800)	0.866 (0.757)	0.964 (0.818)	0.870 (0.787)	0.837 (0.788)	1.032 (0.805)	2.805	0.011
Ethnicity: Hispanic	0.093 (0.554)	0.049 (0.557)	0.137 (0.579)	0.131 (0.553)	0.106 (0.543)	0.053 (0.602)	1.054	0.001
Ethnicity: Indian	0.179 (0.598)	0.149 (0.576)	0.219 (0.595)	0.199 (0.611)	0.201 (0.596)	0.272 (0.540)	1.313	0.004
Ethnicity: Middle Eastern	0.484 (0.472)	0.454 (0.465)	0.514 (0.481)	0.463 (0.476)	0.494 (0.460)	0.629 (0.464)	1.876	0.008
CV: Twitter level								
Tweets (log.)	0.227 (0.113)**	0.269 (0.104)***	0.180 (0.134)	0.225 (0.122)*	0.251 (0.110)**	0.205 (0.109)*	1.228	0.003
Followers (log.)	-0.162 (0.096)*	-0.176 (0.081)**	-0.147 (0.107)	-0.158 (0.096)*	-0.156 (0.084)*	-0.160 (0.085)*	0.852	-0.003
Follows (log.)	-0.041 (0.079)	-0.060 (0.082)	-0.021 (0.080)	-0.041 (0.080)	-0.060 (0.082)	-0.036 (0.080)	0.965	0.001
IV: Big Five								
Openness	-0.164 (0.093)*					0.058 (0.108)	1.059	0.001
Extraversion		0.217 (0.089)**				0.333 (0.105)***	1.394	0.005
Conscientiousness			-0.176 (0.095)*			-0.312 (0.098)***	0.732	-0.005
Agreeableness				-0.000 (0.054)		-0.084 (0.070)	0.919	-0.001
Neuroticism					-0.081 (0.053)	-0.070 (0.056)	0.932	-0.001
Year dummies (8 variables)	Yes	Yes	Yes	Yes	Yes	Yes		
Industry dummies (21 variables)	Yes	Yes	Yes	Yes	Yes	Yes		
Observations (clusters)	3,234 (1,348)	3,234 (1,348)	3,234 (1,348)	3,234 (1,348)	3,234 (1,348)	3,234 (1,348)		
Pseudo-R^2	0.268	0.273	0.270	0.265	0.268	0.286		
Classified correctly (%)	95.269	95.362	95.269	95.269	95.207	95.393		
Log Likelihood	-468.543	-465.376	-467.344	-470.089	-468.276	-456.936		
Chi^2 (sig.)	308.008 ***	305.274 ***	300.638 ***	299.368 ***	299.707 ***	323.516 ***		

3.6.2 Excluding Tweets that are not work-related

In another sensitivity analysis, we exclude BAs whose Tweets are not work-related, because the language (and thus, our personality scores) might differ between people who often talk about work and people who rarely talk about work. To perform this analysis, we obtained additional data from Receptiviti, which includes a dimension that measures the degree to which an individual talks about leisure activities ("leisure orientation"). Low scores in leisure orientation can be seen as a proxy for a higher work orientation.

We then perform a median split according to this variable and re-estimate our main analysis with the 50% of BAs who have the lowest leisure orientation (and thus a higher work orientation). While the results reported in Model 2 (Table 3.A1) lose significance because of the strongly reduced sample size (now 1,647 investments by 641 BAs), the effects of extraversion and conscientiousness remain significant ($p < 0.1$), underlining the robustness of our main findings.

3.6.3 Excluding celebrities

Our sample includes various celebrities. These celebrities include "super angels" such as Fabrice Grinda, with a total of 199 investments and approximately 10,000 followers on Twitter; Ron Conway, with a total of 128 investments and 96,000 followers; and Alexis Ohanian with 118 investments and 141,000 followers. However, our sample also includes famous musicians and actors, led by musician Justin Bieber, who has more than 92 million followers on Twitter but also made two investments as a BA. Other famous BAs include Microsoft founder Bill Gates and actor Ashton Kutcher. Celebrities as BAs could differ in their representation on Twitter, mainly because they have a vastly different target audience than "professional" BAs.

To account for potential bias, we exclude all individuals with more than 500,000 followers, reducing our sample to 3,036 investments by 1,296 individuals (Model 3, Table 3.A1). The results about the effects of extraversion and conscientiousness remain robust.

3.6.4. Excluding later-stage investments

As a further sensitivity analysis, we reduce our sample to investments in seed-stage ventures only. Because BAs often invest in the earliest stages of the venture cycle (e.g., Cumming and Zhang, 2019; Dutta and Folta, 2016), it is particularly important to assess whether our results pertain in this setting.

Model 4 (Table 3.A1) shows the results of our main analysis in this reduced sample. While the positive influence of extraversion on syndication persists, the effect of conscientiousness becomes insignificant. This indicates that the effect of conscientiousness is particularly pronounced in the later stages. An explanation might be that in the later stages, more information is available for investors to assess a venture's quality. Hence, syndication loses its importance as a vehicle to reduce investment risk, particularly for conscientious individuals who carefully evaluate this additional information provided by the venture.

3.6.5 Accounting for different compositions at the syndicate level

Previous research on BA investments has highlighted the importance of the syndicate composition. For example, Gompers et al. (2016b) highlight the importance of similarities between personal characteristics in syndication and their effects on subsequent investment performance. They find that investors who share the same ethnic, educational, or career background are more likely to syndicate with each other.

To rule out a potential bias due to differences between syndicates instead of individuals, we aggregate BAs' personality traits at the syndicate level and construct a mean value for every syndicate. We then re-estimate our main model with these syndicate-level scores. The results are reported in Model 5 (Table 3.A1), which also includes standard errors clustered at the syndicate level. The results underline the robustness of our main results. Both extraversion and conscientiousness remain highly significant determinants of syndication ($p < 0.1$). Note that we explore the topic of syndicate composition further in Section 3.7.

3.6.6 Accounting for a potential endogeneity bias

We argue that personality drives syndication. While research in psychology often describes the Big Five to be relatively stable across time, we cannot rule out that syndication influences how individuals present themselves on Twitter, thereby influencing our personality scores (and the language used on Twitter). To address this potential reverse causality and endogeneity bias, we collect large amounts of additional data to perform several sensitivity analyses. We start by downloading all available Twitter statements by the BAs in our sample and dividing these statements according to whether they occurred before or after an individual's first syndication. Then, we calculate for each BA two personality scores: the first one is based on the Tweets that occurred before the first syndication, and the second is based on the Tweets that occurred after the first syndication. This approach enables us to analyze whether syndication influences our Twitter-based measures of personality.

Our sample decreases in size for multiple reasons. First, we were not able to calculate scores before syndication for every individual because (1) some individuals engaged in syndication before they became active on Twitter, (2) Twitter only allows the retrieval of the latest 3,200 Tweets per individual (i.e., for individuals who are very active on Twitter, we were not able to determine a score before syndication because of the many Tweets that occurred after their first syndication), and (3) we were only able to calculate before and after personality scores for those businesses where we had at least 300 words before and 300 words after syndication. In total, our sample is reduced to 829 investments by 572 BAs.

In the regression results displayed in Table 3.A2 (Appendix), our dependent variables are the Twitter-based personality scores after syndication. Our main independent variable is the syndication dummy, and our control variables are the same as in previous regressions. Furthermore, we control for the respective personality scores before syndication. The syndication dummy is insignificant for all personality measures except for agreeableness, making reverse causality an unlikely explanation for our main findings regarding the effects of extraversion and conscientiousness.

To further explore a potential endogeneity bias, we performed a propensity score matching (PSM) using Stata's "psmatch2" command and performed a single nearest-neighbor matching without replacement. We included all venture characteristics as confounders (independent variables). The PSM thus identified the 161 deals with syndication that were the most similar to the 161 deals without syndication using the independent variables 'amount raised (log.)', 'venture: age (log.)', 'venture: no. of employees', 'venture: no. of founders', 'venture: location US', 'venture: location EU', and 'round: seed-stage'. We then compared the mean values in both groups (Table not shown). The comparison shows that syndicated deals show significantly higher values in extraversion than non-syndicated deals, further underlining the robustness of our result pertaining to extraversion. However, the values for conscientiousness do not differ significantly between the groups, possibly because of the small sample size.

3.6.7 Accounting for differences across countries and states

While our sample is US-centric (92.5% of the BAs are US-based), differences across countries might influence syndication behavior. Since prior research suggests that culture is likely to be an important contextual factor for BA investments and syndication (e.g., Brush et al., 2002; Cumming and Zhang, 2019; Dai and Nahata, 2016), we include the cultural dimensions of Hofstede as control variables in our models.

To rule out any confounding influences of culture on syndication, we conduct multiple robustness checks that are reported in the Appendix (Table 3.A3). Model 1 displays a reassessment of the main analysis that includes country dummies to account for any differences across countries. Model 2 displays a subsample analysis that only considers BAs located in the US. Both models underline the robustness of the main results.

Model 3 focusses on ventures located in the US. To rule out differences in the syndication behavior according to the region where the target venture is located, we control for whether the venture is located in San Francisco (including Palo Alto, Mountain View) or New York. The reference category for the venture's location dummies is "Venture: Location rest of the US". The main results do not change. Interestingly, we find that syndication is more likely for San Francisco-based ventures and less likely for targets located in New York.

3.7 Further exploratory analyses

In these further explanatory analyses, we change the dependent variable and assess how a BA's personality influences various important outcome variables.

3.7.1 Further analyses regarding syndicate size, lead investor and syndicate composition

This section focuses on whether and how BAs' personalities influence different syndicate characteristics, such as the syndicate size, hierarchy, and composition.

Previous research in the VC context has investigated the determinants of syndicate size (e.g., Cumming et al., 2005; De Vries and Block, 2011). Analogously, we investigate how BA personality relates to the size of the syndicate. To this end, we construct an ordinal variable *syndicate size* consisting of four different classes: (1) "Syndicates" with a size of 1 (= the angel investors alone) (5.0% of observations); (2) syndicates with 2 to 5 investors (46.1% of observations); (3) syndicates with 6 to 10 investors (32.2% of observations); and (4) syndicates with more than 10 investors (16.7% of observations). To investigate the effect of BA personality on syndicate size, we estimate a multinomial logistic regression with (1) as the base group. The results are displayed in Table 3.5, Model 1. In line with our prior findings, the results show that investors higher in extraversion have a general preference for syndication, irrespective of the syndicate size. Likewise, investors who are higher in conscientiousness have a lower preference for syndication, irrespective of the syndicate size. This supports our main findings and illustrates that further distinguishing between small and large syndicates does not alter our main findings. However, the results reveal further interesting patterns. For example, the effect of extraversion decreases in magnitude and significance with the increasing syndicate size, whereas the effect of conscientiousness increases in magnitude and becomes more negative with the increasing syndicate size.

Since the variable *syndicate size* is ordinal, an ordered logistic regression would be another alternative. However, using an ordered logit model requires that the assumption of proportional odds is not violated. We thus performed an approximate likelihood-ratio test of proportionality of odds across response categories using Stata's "omodel" command. The test indicates that the assumption is violated and that a standard ordered logit model is inappropriate. Hence, we used a generalized ordered logit model which does not rely on the assumption of proportional odds. The results are reported in Table 3.A4 in the Appendix. The results show that the effects of extraversion and conscientiousness are mainly due to the first group (deals without syndication), underlining the robustness of our main results. However, the nuances between groups are not as pronounced as in the multinomial ordered logistic regression. While the group between 2 to 5 investors has lower conscientiousness, personality does not seem to impact syndication in larger syndicates. Please also note that the largest group is left out of the model as a reference group.

Another important characteristic of a syndicate is the presence of a lead investor. The lead investor signals to syndicate partners that he or she fully backs the deal with his or her reputation, often has the largest equity stake in the syndicate, and often invites follow-on investors to the syndicate (Gompers et al., 2016b; Lockett and Wright, 2001; Manigart et al., 2006). Our dataset enables us to analyze whether a BA's personality correlates with being a lead investor. For example, one could expect extraverted BAs to take on this role more often than other BAs because of their outgoing social personality. To test this idea, we collect additional information on lead investor status from Crunchbase and constructed the dummy variable *lead investor*, which captures whether a particular BA acts as a lead investor (= 1) or not (= 0). Unfortunately, this information is not disclosed for every investment. Overall, we can determine the lead investor status for 893 syndicated deals. We then estimate a logistic regression (Table 3.5, Model 2) with the variable lead investor as the dependent variable. The results do not indicate a relationship between BA personality and lead investor status.

Finally, there are multiple investor types involved in syndication. These include BAs, VC firms, corporate VCs, and others. While our main analysis does not distinguish between investor types, the BA personality might also influence the composition of the type of other partners that are part of the syndicate. For example, BAs low in conscientiousness could be particularly likely to enter a syndicate together with a VC firm, which typically has many resources to conduct a careful venture screening and selection. Therefore, we construct a categorical variable *syndicate composition* from Crunchbase, which considers whether the BA invests (1) alone, (2) together with other BAs, (3) together with VC funds, or (4) together with other BAs and/or VCs and/or other entities (e.g., corporate VCs). We estimate a multinomial regression, and the results are displayed in Table 3.5, Models 3 to 5. The results reveal significant effects for both extraversion and conscientiousness across all three models. This underlines that extraversion increases the likelihood of syndication and conscientiousness reduces the likelihood of syndication, irrespective of the composition of the syndicate.

3.7.2 Further analyses regarding venture success and BA exit

An interesting question is whether and how BA personality relates to venture success. Even though the mechanisms between personality and investment success are less clear and often indirect, prior research has identified that some personality traits are correlated with investment success. For example, Durand et al. (2008) find an effect of extraversion on the portfolio performance of an investor.

To explore the relationship between BA personality and investment or venture success, we construct several proxies.

Our first measure is the venture's ability to attract a second round of funding (e.g., Ter Wal et al., 2016). We collect additional data from Crunchbase on the presence of follow-up funding rounds. The dummy variable *follow-up round* captures whether a second funding round exists (= 1) or not (= 0). In Table 3.6, Model 1, we estimate a logistic regression with *follow-up round* as the dependent variable. The results show that while syndication, the amount raised, and the individual age of the BA are correlated with the existence of a follow up round, BA personality does not seem to have a significant effect.

Another established criterion of venture success is whether a successful exit via a trade sale or an IPO occurred (Tian, 2012). The variable *successful venture exit* captures this situation and indicates whether the venture was acquired or went public (= 1) or not (= 0). Data on this variable is obtained from Crunchbase and was collected as of January 2018. Similar to the previous models, we do not find a significant correlation between BA personality and venture success (Table 3.6, Model 2).

Next to a successful exit via trade sale or IPO, we consider the respective BA's exit from the venture as another important outcome variable (Cumming et al., 2016). Data on the BA exit are from Crunchbase; the variable *BA exit* captures whether the BA exited the venture before January 2018 (= 1) or not (= 0). Unfortunately, Crunchbase does not specify the exact method of exit. Again, the results indicate that personality does not seem to play a major role here and reveal only a weak negative effect of neuroticism on BA exit (Table 3.6, Model 3).

As a final proxy for venture success, we consider whether the venture is still active as of January 2018 (= 1) or closed (= 0). This variable captures *venture survival.* Information is again obtained from Crunchbase. In line with the other proxies above, the results do not show a significant connection between personality and *venture survival* (Table 3.6, Model 4).

One may argue that syndication mediates the effects of the Big Five on venture success. To test this idea, we estimated two additional models for each dependent variable. One model includes the Big Five; the other one the syndication dummy. The results are shown in Table 3.A5 in the Appendix. While syndication affects some measures of venture success, the results indicate that there seems to be no consistent and meaningful relationship between the Big Five and venture success. Also, the effect of the Big Five on venture success does not seem to be mediated by syndication.

In a nutshell, the relationship between BA personality and venture success seems to be complex and not as straightforward as the relationship between BA personality and syndication.

Table 3.5: Further analyses of syndicate characteristics

This table shows multiple analyses that explore the relationship between personality and syndicate size, hierarchy, and composition. Models 1 to 3 display the results of a multinomial regression with different syndicate sizes as the dependent variable. The comparison group are investments with a syndicate size of 1 (no syndication took place). Model 4 displays the results of logistic regression with lead investor as the dependent variable. Models 5 to 7 display the results of a multinomial regression with different syndicate compositions as the dependent variable. The comparison group are investments with where the investor invests alone. All variables are defined in Table 3.1. Coefficients are reported with robust standard errors clustered by BAs in parentheses. Significance levels are denoted by asterisks, *** 1%, ** 5%, and * 10% (p -values are two-tailed).

	Model 1			**Model 2**	**Model 3**	**Model 4**	**Model 5**
Dependent variable	Syndicate size: 2–5	Syndicate size: 6–10	Syndicate size: 10+	Lead investor	Syn. composition: Only BAs	Syn. composition: BAs and VCs	Syn. Composition: BAs and others
Variables	*Logit (SE)*	*Logit SE*	*Logit SE*	*Logit SE*	*Logit (SE)*	*Logit SE*	*Logit SE*
CV: Venture level							
Amount raised (log.)	0.755 (0.083)***	1.040 (0.084)***	1.550 (0.102)***	-1.145 (0.109)***	0.315 (0.084)***	1.277 (0.095)***	1.264 (0.114)***
Venture: Age (log.)	0.344 (0.425)	0.936 (0.433)**	-0.508 (0.453)	-0.061 (0.431)	0.580 (0.467)	0.334 (0.429)	0.632 (0.473)
Venture: No. of employees	0.023 (0.082)	-0.032 (0.088)	0.046 (0.089)	-0.061 (0.097)	0.091 (0.087)	-0.043 (0.083)	0.004 (0.106)
Venture: No. of founders	0.416 (0.135)***	0.468 (0.138)***	0.357 (0.140)**	-0.030 (0.098)	0.294 (0.134)**	0.499 (0.144)***	0.468 (0.158)***
Venture: Location US	0.156 (0.479)	1.180 (0.529)**	0.245 (0.568)	-0.047 (0.499)	-0.087 (0.500)	0.489 (0.490)	2.440 (0.999)**
Venture: Location EU	0.114 (0.582)	0.593 (0.671)	-16.274 (0.716)***	0.680 (0.665)	0.009 (0.670)	0.210 (0.595)	2.167 (1.133)*
Round: Seed-stage	0.259 (0.198)	0.788 (0.208)***	0.735 (0.223)***	-1.623 (0.233)***	0.028 (0.216)	0.623 (0.198)***	0.705 (0.247)***
CV: Investor level							
Previous inv. (log.)	0.496 (0.092)***	0.397 (0.093)***	0.359 (0.100)***	-0.260 (0.086)***	0.336 (0.099)***	0.493 (0.094)***	0.532 (0.107)***
BA: Age (log.)	-0.565 (0.467)	-0.903 (0.504)*	-2.032 (0.576)***	1.874 (0.513)***	-0.376 (0.495)	-0.952 (0.489)*	-0.852 (0.595)
BA: Residence US	0.867 (0.465)*	0.590 (0.527)	1.020 (0.622)	-0.796 (0.485)	0.891 (0.523)*	0.741 (0.509)	1.641 (0.694)**
Male	0.010 (0.592)	-0.347 (0.556)	-0.076 (0.631)	0.577 (0.439)	-0.316 (0.590)	-0.116 (0.554)	0.162 (0.609)
Education: Business	-0.026 (0.209)	-0.069 (0.223)	-0.259 (0.241)	0.127 (0.226)	-0.257 (0.220)	0.074 (0.216)	-0.076 (0.251)
Education: Tec/Sci	0.291 (0.210)	0.414 (0.223)*	0.296 (0.241)	-0.268 (0.237)	0.224 (0.219)	0.430 (0.213)**	0.078 (0.252)
Education: PhD	0.254 (0.319)	0.448 (0.331)	0.224 (0.355)	-0.853 (0.311)***	0.020 (0.338)	0.453 (0.327)	0.389 (0.369)
CV: Twitter level							
Tweets (log.)	0.206 (0.110)*	0.175 (0.116)	0.325 (0.122)***	-0.031 (0.115)	0.179 (0.106)*	0.227 (0.116)*	0.231 (0.134)*
Followers (log.)	-0.177 (0.087)**	-0.134 (0.089)	-0.183 (0.093)**	0.125 (0.079)	-0.207 (0.085)**	-0.155 (0.093)*	-0.127 (0.105)
Follows (log.)	-0.036 (0.081)	-0.025 (0.085)	-0.053 (0.091)	-0.036 (0.091)	0.008 (0.088)	-0.037 (0.082)	-0.140 (0.092)
IV: Big Five							
Openness	0.090 (0.108)	0.007 (0.116)	0.020 (0.122)	0.015 (0.133)	0.039 (0.111)	0.060 (0.113)	0.081 (0.142)
Extraversion	0.367 (0.105)***	0.277 (0.111)**	0.268 (0.116)**	-0.032 (0.138)	0.268 (0.113)**	0.346 (0.108)***	0.341 (0.128)***
Conscientiousness	-0.272 (0.099)***	-0.369 (0.105)***	-0.394 (0.115)***	0.122 (0.109)	-0.248 (0.106)**	-0.325 (0.099)***	-0.403 (0.123)***
Agreeableness	-0.099 (0.069)	-0.071 (0.072)	-0.031 (0.076)	0.045 (0.080)	-0.048 (0.073)	-0.094 (0.071)	-0.098 (0.082)
Neuroticism	-0.073 (0.057)	-0.054 (0.061)	-0.080 (0.066)	0.069 (0.063)	-0.066 (0.061)	-0.056 (0.058)	-0.141 (0.071)**
Hofstede: Culture (4)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnicity dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies (8)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies (21)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (clusters)	3,234 (1,348)			1,118 (635)	3,234 (1,348)		
Pseudo-R²	0.139			0.330	0.192		
Log Likelihood	-3,260.123			-371.669	-2,259.289		
Chi² (sig.)	13,679.859 ***			298.405 ***	2,772.930 ***		

Table 3.6: Further analyses on venture success and BA exit

This table shows multiple analyses that explore the relationship between personality and investment success. We use different proxies to measure investment success. Model 1 shows the results of a logit regression with the existence of a follow-up round of financing as the dependent variable. Model 2 shows the results of a logistic regression, where the dependent variable captures whether the venture was acquired via a trade sale or went public via an IPO. Model 3 shows the results of a logistic regression, where the dependent variable captures whether the BA eventually exited from the venture. Model 4 shows the results of a logistic regression with venture survival as the dependent variable. All variables are defined in Table 3.1. Coefficients are reported with robust standard errors clustered by BAs in parentheses. Significance levels are denoted by asterisks, *** 1%, ** 5%, and * 10% (p - values are two-tailed).

	Model 1	**Model 2**	**Model 3**	**Model 4**
Dependent variable	Follow-up round exists	Successful venture exit	BA exit	Venture survival
Variables	*Logit (SE)*	*Logit SE*	*Logit SE*	*Logit SE*
Syndication (dummy)	2.502 (0.214)***	0.479 (0.233)**	0.195 (0.234)	0.023 (0.325)
CV: Venture level				
Amount raised (log.)	0.294 (0.059)***	0.238 (0.049)***	0.224 (0.049)***	-0.075 (0.070)
Venture: Age (log.)	-0.181 (0.270)	0.347 (0.215)	-0.109 (0.218)	1.047 (0.314)***
Venture: No. of employees	0.385 (0.085)***	-0.085 (0.041)**	-0.077 (0.039)**	0.638 (0.107)***
Venture: No. of founders	0.178 (0.074)**	0.220 (0.044)***	0.210 (0.042)***	-0.084 (0.062)
Venture: Location US	0.535 (0.302)*	0.744 (0.311)**	0.589 (0.315)*	-1.616 (0.683)**
Venture: Location EU	0.420 (0.528)	0.691 (0.398)*	0.509 (0.410)	0.961 (1.305)
Round: Seed-stage	0.114 (0.159)	0.054 (0.107)	0.233 (0.107)**	-0.306 (0.168)*
CV: Investor level				
Previous inv. (log.)	-0.083 (0.053)	0.020 (0.035)	0.017 (0.038)	-0.076 (0.071)
BA: Age (log.)	-0.684 (0.367)*	-0.287 (0.238)	-0.506 (0.246)**	1.121 (0.406)***
BA: Residence US	0.255 (0.344)	0.749 (0.364)**	0.746 (0.319)**	1.253 (0.399)***
Male	0.165 (0.294)	-0.097 (0.185)	-0.208 (0.182)	-0.193 (0.427)
Education: Business	0.183 (0.149)	0.077 (0.098)	0.030 (0.099)	-0.028 (0.150)
Education: Tec/Sci	0.243 (0.157)	-0.048 (0.105)	-0.036 (0.107)	-0.144 (0.176)
Education: PhD	0.013 (0.198)	0.102 (0.118)	0.075 (0.115)	0.071 (0.198)
CV: Twitter level				
Tweets (log.)	0.044 (0.063)	0.022 (0.040)	0.014 (0.042)	-0.031 (0.075)
Followers (log.)	0.009 (0.044)	0.035 (0.028)	0.037 (0.029)	-0.011 (0.056)
Follows (log.)	0.044 (0.058)	-0.063 (0.040)	-0.072 (0.041)*	0.058 (0.065)
IV: Big Five				
Openness	0.030 (0.075)	-0.021 (0.052)	-0.006 (0.052)	-0.067 (0.076)
Extraversion	0.009 (0.068)	-0.044 (0.051)	-0.064 (0.050)	-0.004 (0.084)
Conscientiousness	-0.073 (0.077)	-0.005 (0.049)	-0.052 (0.052)	-0.047 (0.072)
Agreeableness	0.011 (0.042)	0.011 (0.028)	0.000 (0.029)	0.035 (0.047)
Neuroticism	-0.056 (0.039)	-0.028 (0.028)	-0.055 (0.029)*	0.050 (0.048)
Hofstede: Culture (4)	Yes	Yes	Yes	Yes
Ethnicity dummies (5)	Yes	Yes	Yes	Yes
Year dummies (8)	Yes	Yes	Yes	Yes
Industry dummies (21)	Yes	Yes	Yes	Yes
Observations (clusters)	3234 1,348	3146 1,323	3137 1,320	3082 1,305
Pseudo-R^2	0.196	0.136	0.121	0.177
Log-Likelihood	-825.247	-1633.077	-1597.685	-709.871
Chi^2 (sig.)	382.180 ***	449.497 ***	388.667 ***	304.726 ***

3.8 Conclusion

The syndication decision of VC firms has been assessed frequently and has been explained from financial, networking, and resource-based perspectives. Syndication is equally or even more important to BAs, who differ from VC firms. We show that considering the personality traits of BAs significantly contributes to explaining their decision to syndicate their investments. Measuring personality through a novel, comprehensive language analysis based on digital footprints in Twitter statements (Boyd and Pennebaker, 2017; Obschonka and Fisch, 2018), we show that BAs with high values of extraversion are more likely to engage in syndication, whereas high values of conscientiousness reduce the likelihood of syndication. In other words, by analyzing public Tweets of BAs, we can predict a particular aspect of their investment decisions that is characteristic of their personality. Hence, such digital footprints might reveal private information of personal patterns in investment behavior.

Our study also has some limitations. For example, we cannot completely rule out a potential selection bias with regard to the BAs included in our sample, even though we used a broad sample. It might be the case that only BAs with a specific personality profile have a Twitter account, which would bias our results. Additionally, we cannot fully rule out reverse causality because we do not have longitudinal data available that would allow us to use panel estimations.

Our study opens several avenues for future research. While syndication is an important and very widespread aspect of new venture finance, an equally interesting aspect would be the interplay between the investor's personality and the eventual success of the investment. While our further analyses indicate that a relationship between the Big Five personality characteristics of the BA and venture success seems to be absent, a more fine-grained analysis of how and when BA personality relates to venture success may be warranted. For example, it would be interesting to assess whether overconfident BAs are more likely to invest in ventures that will eventually fail than BAs who are less overconfident. Another interesting question is whether our findings can be extended to the general population of VC firms. While being institutional investors, investment decisions in VC firms are also often carried out by individuals. It is thus likely that the personality of their investment managers also has an impact on their investment decision. Additionally and relatedly, the impact of the investor's personality might go beyond the decision to syndicate and could potentially affect the target selection or investment sum.

3.9 Appendix

Table 3.A1: Sensitivity analyses using different estimation techniques and making changes to the sample

This table shows several sensitivity analyses using syndication (dummy) as the dependent variable. Model 1 shows the results of a penalized likelihood estimation using the Firth method to account for a potential bias by rare events. Model 2 shows the results of a logit regression based on a subsample that only includes more work-related Tweets. We identified these Tweets based on another Recitpiviti dimension ("leisure orientation"). We performed a median split and categorized those investors as more work-related, which showed scores below the median in the dimension of leisure orientation. Model 3 shows the results of a logit regression based on a subsample in which celebrities with more than 500,000 Twitter followers are excluded. Model 4 shows the results of a logit regression based on a subsample of firms in the seed-stage. Model 5 shows the results of a logit regression with personality variables aggregated on the syndicate level. Model 1 does not include clustered standard errors because the estimation method does not allow for clustering. In Model 5, standard errors are clustered at the syndicate level, while Models 2, 3, and 4 include clustered standard errors at the BA level. All variables are defined in Table 3.1. Significance levels are denoted by asterisks, *** 1%, ** 5%, and * 10% (p-values are based on two-tailed tests).

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Variables	*Logit (SE)*	*Logit SE*	*Logit SE*	*Logit SE*	*Logit SE*
CV: Venture level					
Amount raised (log.)	0.847 (0.074)***	0.986 (0.113)***	0.898 (0.084)***	1.039 (0.114)***	0.902 (0.085)***
Venture: Age (log.)	0.374 (0.408)	-0.023 (0.519)	0.406 (0.432)	0.097 (0.563)	0.412 (0.427)
Venture: No. of employees	0.007 (0.080)	-0.055 (0.105)	-0.007 (0.089)	0.039 (0.147)	0.006 (0.088)
Venture: No. of founders	0.408 (0.099)***	0.328 (0.143)**	0.448 (0.144)***	0.671 (0.212)***	0.429 (0.142)***
Venture: Location US	0.413 (0.431)	0.279 (0.686)	0.329 (0.539)	-0.183 (0.758)	0.345 (0.510)
Venture: Location EU	0.117 (0.567)	-0.160 (0.783)	0.097 (0.635)	-0.703 (0.864)	0.074 (0.647)
Round: Seed-stage	0.430 (0.201)**	0.227 (0.303)	0.403 (0.206)**		0.457 (0.215)**
CV: Investor level					
Previous inv. (log.)	0.434 (0.098)***	0.304 (0.114)***	0.424 (0.106)***	0.630 (0.142)***	0.457 (0.101)***
BA: Age (log.)	-0.808 (0.473)*	-1.604 (0.727)**	-0.601 (0.482)	-0.557 (0.570)	-0.871 (0.458)*
BA: Residence US	0.819 (0.458)*	0.308 (0.756)	0.888 (0.470)*	1.225 (0.546)**	0.898 (0.508)*
Male	-0.040 (0.497)	0.009 (0.579)	-0.059 (0.661)	0.286 (0.736)	-0.159 (0.532)
Education: Business	-0.069 (0.197)	0.215 (0.310)	-0.001 (0.216)	-0.108 (0.274)	-0.077 (0.202)
Education: Tec/Sci	0.313 (0.206)	0.464 (0.307)	0.288 (0.218)	0.417 (0.284)	0.316 (0.202)
Education: PhD	0.292 (0.307)	0.818 (0.473)*	0.166 (0.330)	0.744 (0.496)	0.300 (0.317)
CV: Twitter level					
Tweets (log.)	0.537 (0.079)**	0.380 (0.142)***	0.080 (0.092)	0.192 (0.126)	0.185 (0.084)**
Followers (log.)	-0.153 (0.056)***	-0.155 (0.098)	-0.055 (0.089)	-0.147 (0.111)	-0.157 (0.062)**
Follows (log.)	-0.034 (0.078)	-0.157 (0.130)	-0.007 (0.084)	-0.054 (0.110)	-0.030 (0.077)
IV: Big Five					
Openness	-0.053 (0.107)	0.054 (0.173)	-0.002 (0.104)	-0.086 (0.145)	
Extraversion	0.315 (0.097)***	0.290 (0.164)*	0.289 (0.104)***	0.471 (0.151)***	
Conscientiousness	-0.294 (0.095)***	-0.295 (0.162)*	-0.322 (0.103)***	-0.205 (0.134)	
Agreeableness	-0.077 (0.066)	-0.176 (0.110)	-0.112 (0.073)	-0.157 (0.099)	
Neuroticism	-0.065 (0.053)	-0.122 (0.095)	-0.038 (0.058)	-0.080 (0.073)	
IV: Big Five (mean per synd.)					
Openness (mean per synd.)					0.072 (0.155)
Extraversion (mean per synd.)					0.461 (0.137)***
Conscientiousness (mean per synd.)					-0.445 (0.127)***
Agreeableness (mean per synd.)					-0.137 (0.108)
Neuroticism (mean per synd.)					-0.083 (0.077)
Hofstede: Culture (4 variables)	Yes	Yes	Yes	Yes	Yes
Ethnicity dummies (5 variables)	Yes	Yes	Yes	Yes	Yes
Year dummies (8 variables)	Yes	Yes	Yes	Yes	Yes
Industry dummies (21 variables)	Yes	Yes	Yes	Yes	Yes
Observations (clusters)	3,234 (-)	1647 (641)	3036 (1,296)	1967 (998)	3234 (1,744)
Pseudo-R²	-	0.320	0.293	0.365	0.295
Log-Likelihood	-369.080	-233.443	-422.578	-253.004	-451.416
Chi² (sig.)	245.850 ***	346.093 ***	307.703 ***	239.802 ***	278.389 ***

Table 3.A2: Sensitivity analyses to account for a potential endogeneity bias

This table reports the results of an analysis to address the issue of a potential endogeneity bias so (i.e., the Tweets in our sample might be influenced by previous syndication). We, therefore, collected data for each individual and divided the Tweets according to whether they took place before or after syndication. Each model presented uses the respective Big Five dimension with values achieved after syndication as the dependent variable. The independent variables are generated based on Tweets before syndication. The main independent variable in this model is the syndication dummy. An insignificant dummy indicates that syndication does not significantly influence the after scores, even when controlling for the before scores. The models display the results of an OLS regression. Because before and after information is not available for every individual, the sample is reduced to 829 investments by 572 BAs. All variables are defined in Table 3.1. Coefficients are reported with robust standard errors clustered by BAs in parentheses. Significance levels are denoted by asterisks, *** 1%, ** 5%, and * 10% (p -values are two-tailed).

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Dependent variable	Openness (after synd.)	Extraversion (after synd.)	Conscientiousness (after synd.)	Agreeableness (after synd.)	Neuroticism (after synd.)
Variables	*Logit (SE)*	*Logit SE*	*Logit SE*	*Logit SE*	*Logit SE*
Syndication (dummy)	0.067 (0.074)	-0.000 (0.050)	-0.107 (0.118)	0.248 (0.146)*	-0.080 (0.058)
CV: Venture level					
Amount raised (log.)	-0.002 (0.011)	-0.005 (0.012)	-0.013 (0.018)	-0.028 (0.030)	0.008 (0.012)
Venture: Age (log.)	0.034 (0.040)	0.038 (0.048)	-0.107 (0.069)	0.052 (0.092)	0.024 (0.040)
Venture: No. of employees	-0.006 (0.010)	0.003 (0.011)	0.041 (0.016)**	-0.051 (0.026)*	0.001 (0.010)
Venture: No. of founders	-0.003 (0.011)	-0.014 (0.012)	0.007 (0.018)	0.006 (0.027)	-0.011 (0.011)
Venture: Location US	-0.147 (0.058)**	-0.047 (0.051)	0.138 (0.100)	0.046 (0.118)	0.012 (0.064)
Venture: Location EU	0.005 (0.107)	-0.026 (0.080)	0.052 (0.188)	0.380 (0.237)	-0.116 (0.098)
Round: Seed-stage	-0.015 (0.026)	0.024 (0.026)	-0.007 (0.043)	-0.008 (0.062)	0.011 (0.027)
CV: Investor level					
Previous inv. (log.)	0.007 (0.023)	-0.037 (0.026)	0.021 (0.036)	-0.100 (0.070)	0.013 (0.024)
BA: Age (log.)	0.073 (0.078)	-0.147 (0.090)	0.127 (0.129)	-0.188 (0.236)	0.046 (0.086)
BA: Residence US	0.053 (0.074)	0.049 (0.080)	-0.200 (0.121)*	0.257 (0.291)	0.014 (0.073)
Male	-0.169 (0.058)***	-0.194 (0.057)***	-0.030 (0.098)	-0.406 (0.154)***	0.082 (0.073)
Education: Business	-0.076 (0.031)**	0.040 (0.035)	0.156 (0.051)***	-0.209 (0.086)**	-0.005 (0.032)
Education: Tec/Sci	-0.029 (0.029)	0.048 (0.032)	0.069 (0.052)	0.199 (0.082)**	-0.085 (0.031)***
Education: PhD	0.020 (0.037)	0.025 (0.054)	0.001 (0.090)	-0.049 (0.105)	0.043 (0.052)
CV: Twitter level					
Tweets (log.)	0.040 (0.017)**	-0.061 (0.017)***	-0.081 (0.028)***	-0.023 (0.042)	-0.004 (0.018)
Followers (log.)	-0.014 (0.012)	0.023 (0.013)*	0.021 (0.015)	0.017 (0.035)	-0.005 (0.012)
Follows (log.)	-0.011 (0.015)	0.029 (0.015)**	0.049 (0.026)*	-0.021 (0.035)	0.013 (0.016)
IV: Big Five					
Openness (before synd.)	0.443 (0.056)***	0.068 (0.058)	0.047 (0.083)	-0.232 (0.151)	-0.042 (0.060)
Extraversion (before synd.)	-0.018 (0.036)	0.412 (0.045)***	0.154 (0.076)**	-0.096 (0.121)	0.039 (0.042)
Conscientiousness (before synd.)	-0.065 (0.034)*	0.052 (0.037)	0.434 (0.066)***	-0.197 (0.094)**	-0.061 (0.036)*
Agreeableness (before synd.)	-0.018 (0.021)	0.041 (0.021)*	-0.070 (0.038)*	0.508 (0.068)***	-0.017 (0.021)
Neuroticism (before synd.)	-0.005 (0.052)	0.046 (0.053)	-0.252 (0.095)***	0.026 (0.133)	0.454 (0.057)***
Hofstede: Culture (4)	Yes	Yes	Yes	Yes	Yes
Ethnicity dummies (5)	Yes	Yes	Yes	Yes	Yes
Year dummies (8)	Yes	Yes	Yes	Yes	Yes
Industry dummies (21)	Yes	Yes	Yes	Yes	Yes
Observations (clusters)	829 (572)	829 (572)	829 (572)	829 (572)	829 (572)
R^2 (sig.)	0.372 ***	0.396 ***	0.482 ***	0.501 ***	0.385 ***

Table 3.A3: Exploring differences across countries and states in more detail

This table reports the results of an analysis to address differences that arise from a different origin. Model 1 displays a reassessment of the main analysis that additionally includes country dummies to account for any differences in syndication behavior across countries. Model 2 displays a subsample analysis that only considers BA's located in the US. Model 3 further controls for the location of the investment target within the US and only includes targets that are located in the US. The reference category for the venture's location dummies is "Venture: Location rest of the US". All variables are defined in Table 3.1. Coefficients are reported with robust standard errors clustered by BAs in parentheses. Significance levels are denoted by asterisks, ∗∗∗ 1%, ∗∗ 5%, and ∗ 10% (p -values are two-tailed).

	Model 1	**Model 2**	**Model 3**
Variables	*Logit (SE)*	*Logit SE*	*Logit SE*
CV: Venture level			
Amount raised (log.)	0.912 (0.081)***	0.929 (0.086)***	0.898 (0.087)***
Venture: Age (log.)	0.403 (0.395)	0.312 (0.452)	0.569 (0.432)
Venture: No. of employees	-0.008 (0.085)	-0.042 (0.087)	-0.063 (0.090)
Venture: No. of founders	0.416 (0.141)***	0.388 (0.142)***	0.333 (0.139)**
Venture: Location US	0.693 (0.495)	0.611 (0.586)	-
Venture: Location EU	0.152 (0.615)	0.004 (0.763)	-
Round: Seed-stage	0.474 (0.202)**	0.506 (0.212)**	0.442 (0.212)**
Venture: Location San Francisco	-	-	1.078 (0.234)***
Venture: Location New York	-	-	0.569 (0.288)**
CV: Investor level			
Previous inv. (log.)	0.463 (0.089)***	0.463 (0.093)***	0.410 (0.103)***
BA: Age (log.)	-1.060 (0.475)**	-1.232 (0.516)**	-0.934 (0.497)*
BA: Residence US	-	-	0.885 (0.344)***
Male	-0.122 (0.543)	-0.127 (0.567)	-0.267 (0.634)
Education: Business	-0.124 (0.211)	-0.101 (0.227)	-0.062 (0.217)
Education: Tec/Sci	0.291 (0.218)	0.231 (0.231)	0.197 (0.225)
Education: PhD	0.329 (0.331)	0.486 (0.361)	0.354 (0.346)
CV: Twitter level			
Tweets (log.)	0.180 (0.103)*	0.199 (0.102)**	0.225 (0.101)**
Followers (log.)	-0.170 (0.079)**	-0.174 (0.075)**	-0.167 (0.076)**
Follows (log.)	0.004 (0.083)	0.002 (0.084)	-0.045 (0.086)
IV: Big Five			
Openness	0.085 (0.112)	0.095 (0.117)	0.033 (0.108)
Extraversion	0.372 (0.103)***	0.335 (0.108)***	0.300 (0.109)***
Conscientiousness	-0.338 (0.103)***	-0.358 (0.109)***	-0.298 (0.098)***
Agreeableness	-0.106 (0.073)	-0.082 (0.078)	-0.060 (0.076)
Neuroticism	-0.095 (0.057)*	-0.103 (0.059)*	-0.087 (0.061)
Hofstede: Culture (4)	No	No	No
Ethnicity dummies (5)	Yes	Yes	Yes
Year dummies (8)	Yes	Yes	Yes
Industry dummies (21)	Yes	Yes	Yes
Country dummies (9)	Yes	No	No
Observations (clusters)	3,153 (1,299)	2,992 (1,227)	2,927 (1,303)
Pseudo-R^2	0.265	0.294	0.306
Log-Likelihood	-450.107	-394.635	-398.666
Chi^2 (sig.)	346.436 ***	292.836 ***	305.874 ***

Table 3.A4: Exploring differences in syndicate size further

This table shows the results of a generalized ordered logit model. The comparison group are investments with a syndicate size of more than 10. All variables are defined in Table 3.1. Coefficients are reported with robust standard errors clustered by BAs in parentheses. Significance levels are denoted by asterisks, *** 1%, ** 5%, and * 10% (p -values are two-tailed).

	Model 1		
Dependent variable	Syndicate size: 0	Syndicate size: 2–5	Syndicate size: 6–10
Variables	*Logit (SE)*	*Logit SE*	*Logit SE*
CV: Venture level			
Amount raised (log.)	0.838 (0.078)***	0.492 (0.038)***	0.724 (0.071)***
Venture: Age (log.)	0.282 (0.417)	0.123 (0.148)	-0.937 (0.210)***
Venture: No. of employees	0.033 (0.087)	-0.021 (0.033)	0.028 (0.041)
Venture: No. of founders	0.436 (0.135)***	0.047 (0.036)	-0.093 (0.052)*
Venture: Location US	0.351 (0.488)	0.673 (0.213)***	-0.599 (0.301)**
Venture: Location EU	0.034 (0.608)	-0.207 (0.343)	-16.109 (0.468)***
Round: Seed-stage	0.523 (0.200)***	0.505 (0.092)***	0.219 (0.125)*
CV: Investor level			
Previous inv. (log.)	0.515 (0.093)***	-0.079 (0.033)**	-0.078 (0.045)*
BA: Age (log.)	-0.862 (0.489)*	-0.702 (0.241)***	-1.286 (0.309)***
BA: Residence US	0.921 (0.491)*	-0.141 (0.260)	0.125 (0.382)
Male	-0.124 (0.559)	-0.302 (0.176)*	0.035 (0.235)
Education: Business	-0.096 (0.207)	-0.090 (0.089)	-0.224 (0.111)**
Education: Tec/Sci	0.384 (0.208)*	0.098 (0.098)	0.068 (0.120)
Education: PhD	0.127 (0.326)	0.157 (0.127)	-0.019 (0.144)
CV: Twitter level			
Tweets (log.)	0.204 (0.114)*	0.022 (0.040)	0.117 (0.052)**
Followers (log.)	-0.167 (0.088)*	0.019 (0.030)	-0.001 (0.032)
Follows (log.)	-0.043 (0.080)	-0.005 (0.033)	0.007 (0.046)
IV: Big Five			
Openness	0.147 (0.117)	-0.073 (0.049)	-0.015 (0.056)
Extraversion	0.323 (0.106)***	-0.077 (0.049)	-0.040 (0.056)
Conscientiousness	-0.357 (0.099)***	-0.135 (0.046)***	-0.087 (0.061)
Agreeableness	-0.062 (0.065)	0.041 (0.028)	0.044 (0.033)
Neuroticism	-0.067 (0.055)	0.004 (0.027)	-0.027 (0.034)
Hofstede: Culture (4)	Yes	Yes	Yes
Ethnicity dummies (5)	Yes	Yes	Yes
Year dummies (8)	Yes	Yes	Yes
Industry dummies (21)	Yes	Yes	Yes
Observations (clusters)	3,234 (1,348)		
Pseudo-R^2	0.140		
Log-Likelihood	-3,255.488		
Chi^2 (sig.)	9,226.415 ***		

Table 3.A5: Further analyses on venture success and BA exit

This table shows multiple analyses that explore the relationship between personality and investment success while paying specific attention to a potential mediation by syndicate (dummy). We use different proxies to measure investment success. Model 1 and 2 show the results of a logit regression with the existence of a follow-up round of financing as the dependent variable. Models 3 and 4 show the results of a logistic regression, where the dependent variable captures whether the venture was acquired via a trade sale or went public via an IPO. Models 5 and 6 show the results of a logistic regression, where the dependent variable captures whether the BA eventually exited from the venture. Models 7 and 8 show the results of a logistic regression with venture survival as the dependent variable. All variables are defined in Table 3.1. Coefficients are reported with robust standard errors clustered by BAs in parentheses. Significance levels are denoted by asterisks, *** 1%, ** 5%, and * 10% (p -values are two-tailed).

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Dependent variable	Follow-up round exists		Successful venture exit		BA exit		Venture survival	
Variables	*Logit (SE)*	*Logit (SE)*	*Logit SE*	*Logit SE*	*Logit (SE)*	*Logit (SE)*	*Logit (SE)*	*Logit SE*
Syndication (dummy)		2.495 (0.203)***		0.208 (0.234)		0.041 (0.319)		0.481 (0.233)**
CV: Venture level								
Amount raised (log.)	0.457 (0.056)***	0.267 (0.062)***	0.233 (0.048)***	0.222 (0.049)***	-0.074 (0.067)	-0.079 (0.069)	0.259 (0.048)***	0.236 (0.049)***
Venture: Age (log.)	-0.291 (0.260)	-0.414 (0.267)	-0.109 (0.218)	-0.112 (0.218)	1.047 (0.315)***	1.031 (0.311)***	0.347 (0.216)	0.348 (0.214)
Venture: No. of employees	0.311 (0.077)***	0.353 (0.081)***	-0.078 (0.039)**	-0.078 (0.039)**	0.638 (0.107)***	0.638 (0.107)***	-0.086 (0.041)**	-0.084 (0.041)**
Venture: No. of founders	0.196 (0.073)***	0.114 (0.070)	0.212 (0.042)***	0.211 (0.042)***	-0.083 (0.061)	-0.084 (0.062)	0.224 (0.044)***	0.221 (0.044)***
Venture: Location US	0.425 (0.309)	0.455 (0.311)	0.589 (0.315)*	0.589 (0.319)*	-1.616 (0.682)**	-1.590 (0.696)**	0.738 (0.310)**	0.745 (0.313)**
Venture: Location EU	-0.170 (0.409)	-0.120 (0.454)	0.509 (0.408)	0.510 (0.413)	0.962 (1.304)	1.020 (1.334)	0.683 (0.395)*	0.691 (0.399)*
Round: Seed-stage	0.355 (0.146)**	0.278 (0.152)*	0.237 (0.107)**	0.232 (0.108)**	-0.305 (0.167)*	-0.303 (0.167)*	0.065 (0.107)	0.053 (0.108)
CV: Investor level								
Previous inv. (log.)	0.070 (0.059)	-0.014 (0.063)	0.019 (0.038)	0.010 (0.038)	-0.075 (0.071)	-0.080 (0.067)	0.024 (0.035)	0.015 (0.034)
BA: Age (log.)	-0.927 (0.312)***	-1.039 (0.326)***	-0.507 (0.246)**	-0.503 (0.246)**	1.121 (0.406)***	1.003 (0.400)**	-0.294 (0.238)	-0.266 (0.236)
BA: Residence US	0.270 (0.327)	0.073 (0.326)	0.748 (0.320)**	0.795 (0.321)**	1.254 (0.399)***	1.269 (0.395)***	0.748 (0.364)**	0.777 (0.367)**
Male	-0.210 (0.270)	-0.314 (0.249)	-0.210 (0.182)	-0.187 (0.176)	-0.194 (0.427)	-0.286 (0.433)	-0.099 (0.188)	-0.087 (0.183)
Education: Business	0.111 (0.143)	0.167 (0.143)	0.029 (0.099)	0.018 (0.098)	-0.028 (0.150)	-0.002 (0.148)	0.076 (0.097)	0.078 (0.096)
Education: Tec/Sci	0.108 (0.148)	0.072 (0.151)	-0.033 (0.107)	-0.006 (0.106)	-0.144 (0.175)	-0.133 (0.168)	-0.043 (0.105)	-0.038 (0.105)
Education: PhD	-0.086 (0.184)	-0.138 (0.193)	0.076 (0.115)	0.059 (0.114)	0.071 (0.198)	0.084 (0.195)	0.104 (0.118)	0.096 (0.116)
CV: Twitter level								
Tweets (log.)	0.044 (0.060)	-0.015 (0.061)	0.016 (0.043)	0.022 (0.040)	-0.031 (0.075)	-0.013 (0.069)	0.023 (0.040)	0.016 (0.037)
Followers (log.)	0.031 (0.041)	0.057 (0.044)	0.036 (0.029)	0.030 (0.029)	-0.011 (0.056)	-0.007 (0.057)	0.034 (0.028)	0.033 (0.028)
Follows (log.)	-0.033 (0.060)	-0.003 (0.060)	-0.073 (0.041)*	-0.068 (0.041)*	0.058 (0.065)	0.045 (0.062)	-0.064 (0.040)	-0.058 (0.039)
IV: Big Five								
Openness	-0.070 (0.075)		-0.006 (0.052)		-0.067 (0.076)		-0.021 (0.052)	
Extraversion	0.038 (0.071)		-0.063 (0.050)		-0.004 (0.084)		-0.042 (0.051)	
Conscientiousness	-0.145 (0.078)*		-0.054 (0.052)		-0.048 (0.072)		-0.010 (0.049)	
Agreeableness	0.059 (0.042)		-0.000 (0.029)		0.035 (0.047)		0.010 (0.028)	
Neuroticism	-0.054 (0.043)		-0.056 (0.029)*		0.050 (0.048)		-0.030 (0.028)	
Hofstede: Culture (4)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnicity dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies (8)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies (21)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (clusters)	3,234 (1,348)	3,234 (1,348)	3,137 (1,320)	3,137 (1,320)	3,082 (1,305)	3,082 (1,305)	3,146 (1,323)	3,146 (1,323)
Pseudo-R^2	0.121	0.181	0.120	0.119	0.177	0.175	0.135	0.136
Log Likelihood	-943.900	-880.403	-1,598.055	-1,600.463	-709.873	-711.723	-1,635.135	-1,633.943
Chi² (sig.)	308.799 ***	418.624 ***	388.574 ***	375.861 ***	303.412 ***	283.822 ***	441.979 ***	444.372 ***

Chapter 4

Initial coin offerings (ICOs) to finance new ventures

In an initial coin offering (ICO), new ventures raise capital by selling tokens to a crowd of investors. Often, this token is a cryptocurrency, a digital medium of value exchange based on the distributed ledger technology. Both the number of ICOs and the amount of capital raised have exploded since 2017. Despite attracting significant attention from ventures, investors, and policymakers, little is known about the dynamics of ICOs. This initial study therefore assesses the determinants of the amount raised in 423 ICOs. Drawing on signaling theory, the study explores the role of signaling ventures' technological capabilities in ICOs. The results show that technical white papers and high-quality source codes increase the amount raised, while patents are not associated with increased amounts of funding. Exploring further determinants of the amount raised, the results indicate that some of the underlying mechanisms in ICOs resemble those found in prior research into entrepreneurial finance, while others are unique to the ICO context. The study's implications are multifold and discussed in detail. Importantly, the results enable investors to more accurately understand crucial determinants of the amount raised (e.g., technical white papers, source code quality, token supply, Ethereum-standard). This reduces the considerable uncertainty that investors face when investing in ICOs and enables more informed decision-making

This chapter is based on

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4.1 Introduction

New, innovative ventures require financial resources to succeed (Block et al., 2018a; Gompers and Lerner, 2004). An ICO is a mechanism through which new ventures raise capital by selling tokens to a crowd of investors. Often, this token is a cryptocurrency, a digital medium of value exchange based on the distributed ledger technology (DLT). Currently, the most common type of DLT is the blockchain technology.[8] While DLT, blockchain technology, and cryptocurrency are potentially revolutionary innovations within the monetary and technological fields (e.g., Elnaj, 2018; Swan, 2015), ICOs represent an innovation in entrepreneurial finance. In an ICO, investors buy tokens directly from a new venture; these tokens are intended to become future functional units of the venture's project (e.g., utility function, right to ownership, royalties). ICOs enable startups to raise large amounts of funding with minimal effort while avoiding compliance and intermediary costs (Kaal and Dell'Erba, 2018; Sameeh, 2018).

Due to their novelty, little is known about the dynamics of ICOs from an entrepreneurial finance perspective. Therefore, I seek to introduce the ICO phenomenon to the entrepreneurial finance literature by examining one of the most fundamental questions in an empirical fashion: What factors determine the amount of funding raised in ICOs?

To answer this question, I draw on signaling theory (Spence, 1973), which is concerned with reducing information asymmetry in the investor-investee relationship. ICOs are characterized by a considerable amount of information asymmetry, for example, because ventures are typically in early stages. Additionally, the amount of objective information surrounding ICOs is very low and there is thus considerable potential for fraud (Shifflett and Jones, 2018). Due to the high investment risk involved, the US Securities and Exchange Commission (SEC) issued a warning to investors about ICOs but also acknowledged their innovative potential (SEC, 2017).

To overcome this information asymmetry, signaling theory argues that high-quality ventures should send signals to investors to inform them about the venture's higher quality. In turn, high-quality ventures can attract higher amounts of funding because potential investors will be able to differentiate between ventures of high and low quality (e.g., Connelly, 2011; Spence, 2002). Given the highly technological setting that ICO conducting ventures are engaged in, I argue that high quality, in the ICO context, is reflected by higher technological capabilities. In particular, I explore three indicators that qualify as potential signals of technological capabilities (i.e., patents, technical white papers, and high-quality source code). I also include a wide set of control variables to control for and

[8] While the majority of ICOs use blockchain technology as of 2018, there are also ICOs that use non-blockchain DLTs (D'Anconia, 2017). Even though the terms "DLT" and "blockchain" are often used interchangeably, they are not identical: blockchain is a subcategory of DLT and DLT is the technology behind the tokens offered in ICOs.

explore the role of additional characteristics that the entrepreneurial finance literature has associated with higher amounts of funding raised (and funding success more generally).

This study extends previous research on entrepreneurial finance by introducing ICOs as a new mechanism for innovative ventures to raise capital. While raising capital in an ICO shares similarities with crowdfunding (e.g., Ahlers et al., 2015; Mollick, 2014), several particularities unique to the ICO context exist. For instance, signals of technological capabilities are especially important in the ICO context and significantly impact the amount of funding raised. In addition, this study extends entrepreneurial finance literature that applies signaling theory to the novel context of ICOs (e.g., Baum and Silverman, 2004; Vismara, 2016).

This study's findings also inform potential investors and ventures about how to evaluate or conduct an ICO that attracts more funding. For example, important determinants that investors should consider include factors relating to ventures' technological capabilities (e.g., source code quality, technical white papers). This implies that it may be worthwhile for investors to familiarize themselves with DLT and blockchain technology in order to be able to more accurately understand the technical information provided by the ventures. The results also show that the amount raised is determined by factors that do not seem to relate to ventures' underlying capabilities and are highly specific to the ICO context (e.g., token supply, Ethereum-standard). Identifying and understanding the influence of these factors reduces the considerable uncertainty that investors face and enables more informed investment decision-making. Furthermore, the results inform ventures seeking to raise higher amounts of funding through ICOs about the importance of developing and communicating their technological capabilities, while potential investors are informed about which factors drive up ICO valuations. Finally, policies surrounding ICOs are in early stages of development and will need to be expanded in the future (Zetzsche et al., 2017). This study makes suggestions for policymakers interested in supporting high-quality and discouraging low-quality ventures.

4.2 Description of ICOs and market overview

4.3.1 Detailed description of ICOs

There is no widely accepted definition of ICOs. I propose a rather broad definition that focuses on their role as a means of entrepreneurial finance and define ICOs as a mechanism used by new ventures to raise capital by selling tokens to a crowd of investors. This implies that ICOs utilize a crowdfunding approach and should thus share similarities with crowdfunding. One aspect that makes ICOs novel and unique is the concept of selling tokens. A token corresponds to a unit of value issued by a venture and covers a wide range of applications. Usually, this value refers to tokens either providing a utility or functioning as securities. Hence, "utility tokens" are generally distinguished from "security tokens" even though no legally-binding classification of token types exists (Sameeh, 2018).

Utility tokens, which constitute the majority of ICO tokens, refer to a digital medium that enables the exchange of utility. There are other types of tokens that provide utility, such as reputation or reward tokens, and more token types are likely to emerge in the future (Hill, 2017). Cryptocurrency refers to a digital medium of value exchange and is also referred to as a coin (hence the term "initial coin offering"). A lot of ventures create their own cryptocurrency by issuing tokens that are intended to function as a currency in the venture's own eco-system. Because of this intended utility function, cryptocurrencies can be described as a subcategory of utility tokens even though they are sometimes also referred to as a distinct category. Moreover, cryptocurrencies play an important role in ICOs because ventures sell tokens and accept other cryptocurrencies (mostly Bitcoin and Ether) as payment. These established cryptocurrencies can be traded for regular currencies, which are then used to fund the venture. It is important to note that the venture-issued tokens often do not have a countervalue or real-world usage at the time of the ICO. Instead, they entitle the holder to future participation in a project that uses the tokens in its respective utility-providing function (e.g., Kaal and Dell'Erba, 2018; Russo and Kharif, 2017).

Security tokens' value is derived from a tradeable asset and they function primarily as investment vehicles. As such, they can be equity tokens, which imply ownership or control and resemble traditional stocks, or they may resemble all kinds of traditional securities, entitling the token holder to a share of ownership, dividends, or other financial benefits (Sameeh, 2018).

Regardless of type, one distinguishing feature is that most tokens can be traded in a secondary market after the conclusion of the ICO (e.g., Benedetti and Kostovestky, 2018). A multitude of exchanges have emerged that enable the trade of tokens against other tokens or traditional currencies. Because of the high volatility of prices on these exchanges, this secondary, speculative function of tokens is frequently highlighted in the media (e.g., Adkisson, 2018; Madeira, 2018).

Another salient characteristic is that tokens are built on and thus require the use of DLT. DLT represents a novel and evolving technological innovation to record and share data across multiple data stores (ledgers) (for a detailed description of the technology see Natarajan et al., 2017). ICOs enable startups to raise funding without involving any intermediaries. Due to their, highly technological nature, ICOs are not applicable to every venture. Rather, they only appeal to ventures utilizing DLT, which is a narrow segment of high-tech firms. However, as the adoption of DLT and blockchain increases, ICOs will become a viable vehicle for a broader set of ventures.

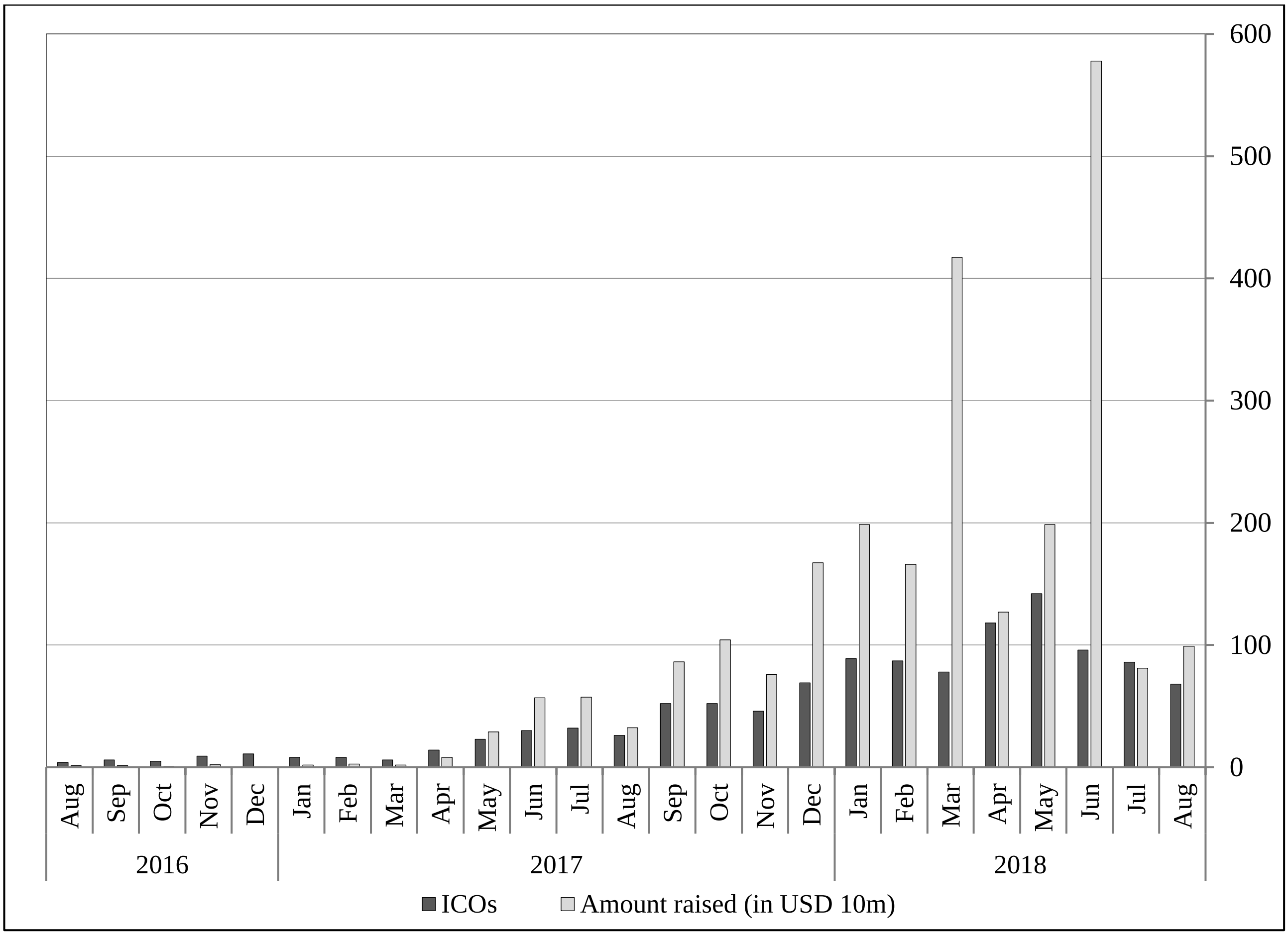
4.3.2 Overview of the ICO market

There is no platform upon which ICOs must occur and there is no compulsory registration for ICOs, making it difficult to keep track of the ICO market. Various websites track ICOs, though most of them are manually curated and rely on user entries. CoinSchedule (www.coinschedule.com) is one of the more established and comprehensive ICO-tracking sites (Economist, 2017; Roose, 2017).

As of September 2018, CoinSchedule reports the occurrence of 1,178 ICOs from January 2016 (first entry) until August 2018, with a total funding volume of 25.1 $b. Figure 4.1 illustrates the market dynamics and shows a rapid increase in both the number of ICOs and the amount of capital raised. CoinSchedule lists 48 ICOs with a capital amount of 0.3 $b in 2016. This number increased to 366 ICOs amounting to 6.2 $b in 2017 and further increased to 18.7 $b raised by 764 ICOs between January and August 2018. Note that ICO funding volumes are influenced by the price levels of the cryptocurrencies accepted as payment (e.g., Bitcoin, Ether).

There is high skewness involved in these figures: The ten largest ICOs accounted for a total of 13.7 $b. These include EOS, which conducted an ICO that lasted 365 days and collected 4.2 $b in June 2018, and Telegram, which develops a blockchain-based messaging service that raised 1.7 $b in a pre-sale in March 2018. Still, with a mean value of 21.4 $m (median: 7.7 $m), the average amount of capital raised is considerable.

Figure 4.1: Number of ICOs and amount raised (in 10 $m).



Notes: Data retrieved from CoinSchedule on September 21st, 2018.

4.3 Conceptual framework: signaling technological capabilities

4.3.1 Overview of signaling theory

Signaling theory is concerned with the reduction of information asymmetry and has been applied to the context of VC (e.g., Busenitz et al., 2005), business angels (e.g., Elitzur and Gavious, 2003), and crowdfunding (e.g., Ahlers et al., 2015; Anglin et al., 2018; Vismara, 2016). Building on the seminal work of Spence (1973), signaling theory argues that high-quality ventures can send signals to potential investors that will inform them about the venture's higher quality. In turn, those ventures are able to attract more funding because of reduced information asymmetry.

Conceptually, signaling theory is comprised of signalers, receivers, and the signal itself. Signalers have a privileged perspective on the underlying quality because they have insider information that is unavailable to outsiders. Signalers then decide whether to communicate this information to outsiders. The signal, observable actions providing information about unobservable attributes, is then sent to the receiver, who interprets the signal into an opinion about the underlying quality of the venture and acts accordingly (Connelly et al., 2011; Spence, 2002).

Signaling theory describes two criteria that a signal must satisfy in order to be an effective means of reducing information asymmetry. First, the signal must be observable. If the receiver does not notice the signal, it will not reduce information asymmetry. Second, the signal must be costly to realize and imitate. These costs do not have to be monetary and can also refer to time, effort, reputation, or foregone earnings. If no cost is involved in producing and sending the signal, it will be easy to imitate and thus will not serve as an effective signal of the signaler's underlying quality (Connelly et al., 2011).

A crucial assumption is that equivalent signals must incur different costs for ventures of higher and lower quality. This leads to a "separating equilibrium" (Bergh et al., 2014; Spence 1973), which occurs if low-quality signalers incur costs that are disproportionately higher than high-quality signalers to convey the same signal (Bergh et al., 2014; Spence, 1973). Assuming rational behavior, this situation separates high- and low-quality signalers, as only high-quality signalers will actually choose to produce the signal. In turn, the receiver bases his selection on the signal because he assumes that only high-quality ventures will produce the signal. Finally, an equilibrium forms if the expected quality of the signal is realized and confirmed (Bergh et al., 2014).

4.3.2 Information asymmetry and the role of technological capabilities in ICOs

Characteristics of signalers and receivers in the ICO context

To apply signaling theory to the ICO context, it is important to describe signalers (i.e., ventures that conduct an ICO) and receivers (i.e., ICO investors) in more detail.

Technical environment. ICOs only suit ventures that (intend to) use DLT, which is a highly technical innovation (Swan, 2015). Understanding the technological complexities and possessing the necessary skills to utilize DLT are thus crucial to ICO ventures (e.g., Chester, 2017; Cohney et al., 2018; Long, 2018). Similarly, investors require some technical expertise or at least the willingness to familiarize themselves with the technical background and application proposed by each venture. This is illustrated in investor's guides that often postulate that understanding the technical background of a project is an important precondition for making an informed decision when investing in ICOs (e.g., Brummer, 2018; Lielacher, 2017; Mulders, 2018; Schwartzkopff, 2018).

Investment risk. ICOs are described as high-risk investments (e.g., SEC, 2017). The reasons are multifold. ICOs typically occur in the early stages of a venture's life cycle (Kaal and Dell'Erba, 2018) and the tokens often do not have any counter value or real-world usage at the time of the ICO (Russo and Kharif, 2017). Also, there is a high potential for fraud in ICOs (e.g., SEC, 2017; Shifflet and Jones, 2018). Because ICO investors seem tolerant of and not discouraged by this higher investment risk, it is reasonable to assume that ICO investors tend to be more risk-prone than noninvestors. Alternatively, they may be able to better mitigate investment risk by performing thorough due diligence before investing.

Absence of disclosure requirements along with anonymity. Formal disclosure requirements in ICOs are largely absent (e.g., Kastelein, 2017; Shifflett and Jones, 2018). Furthermore, there are few norms of behavior regarding what information should be disclosed, leading to a situation in which ventures often disclose little information (e.g., Kaal and Dell'Erba, 2018). Adding to this point, one of the major drivers behind the development of DLT (and cryptocurrencies specifically) is the desire to enable anonymous transactions (Nakamoto, 2008). Consequently and historically, the context of DLT (including ICOs) is characterized by a desire for anonymity (e.g., Kastelein, 2017; Poutintsev, 2018). For example, some teams prefer to stay anonymous in ICOs and do not reveal any personal information. Also, most ICOs are pseudonymous, meaning that it is possible to track which account a transaction comes from while the identity of the account holder remains unknown (Kastelein, 2017). While more recently some companies have implemented Know Your Customer (KYC) frameworks that require the identification of sale participants, parts of the ICO community are critical of this practice since they are highly concerned with anonymity and privacy (e.g., Poutintsev, 2018). The slow and fragmented implementation of KYC standards and the pronounced interest in anonymity suggest that investors in ICOs seem to embrace, or at least accept that information is often not as readily available.

Information asymmetry and the need for signaling in ICOs

These characteristics lead to increased uncertainty and establish a high degree of information asymmetry between ventures and investors. Specifically, the reasons for increased uncertainty are threefold:

First, the highly technical environment in which ICOs operate creates uncertainty. For example, the future development and adoption of the distributed ledger technology as a whole are still unclear (e.g., Natarajan et al., 2017). Also, investors with limited technological expertise may find it difficult to understand the technology proposed by a venture without first investing some time and effort. Second, these ventures are typically in early stages, do not yet have a developed project, and there is a high potential for fraud (e.g., Kaal and Dell'Erba, 2018, SEC, 2017). Third, the amount of objective information available in ICOs is low due to the absence of formal disclosure requirements and a greater desire for anonymity. This leads to considerable heterogeneity in the amount and type of information disclosed. Often, the "usual" information that investors typically take into account when evaluating ventures (e.g., venture history, biographies of founders, financial projections) is not available. For example, while most ventures publish some information about the team, this information is often not very rich and may even be inaccurate or fraudulent, as shown by anecdotal evidence of fake profiles (Shifflett and Jones, 2018).

A higher amount of information asymmetry generally leads to a greater need for signaling (e.g., Hsu and Ziedonis, 2013; Kotha et al., 2018). Because the investor-investee relationships in ICOs are characterized by a particularly large amount of information asymmetry, signaling theory provides a suitable framework to explain how ventures could reduce information asymmetry to attract funding.

Signaling technological capabilities to indicate higher quality to investors

The entrepreneurial finance literature assumes that potential investors prefer to invest in high-quality ventures because they are more likely to succeed (e.g., Ahlers et al., 2015; Stuart et al., 1999). I argue that the future success of ICO ventures depends on their technological capabilities. Therefore, higher technological capabilities may correspond to higher quality in ICOs and ventures with higher technological capabilities should have a profound interest in signaling these capabilities to potential investors in order to obtain higher amounts of funding.

Ventures that conduct ICOs build on and utilize DLT, which is necessary for the emission of tokens. DLT and blockchain technology is described as complex, revolutionary, highly disruptive, and capable of enabling an economic shift towards a novel, decentralized economy (e.g., Elnaj, 2018; Swan, 2015). DLT represents a major technological innovation that requires ventures to possess substantial technological capabilities. Understanding the technological complexities of the DLT and possessing the necessary skills to develop it further is a core competency required from ventures that intend to utilize the technology (e.g., Chester, 2017; Cohney et al., 2018; Long, 2018). Most articles that convey investment advice mention the venture's technological competences as a key factor for evaluating the eventual success of an ICO (e.g., Brummer, 2018; Lielacher, 2017; Mulders, 2018; Schwartzkopff, 2018).

This argument is also in line with previous research in entrepreneurial finance, which shows that signaling technological capabilities or "intellectual capital" is crucial for reducing information asymmetry in the investor-investee relationship (e.g., Ahlers et al., 2015; Hsu and Ziedonis, 2013). Higher technological capabilities are assumed to be related to greater innovative potential, and so are crucial for venture success, especially in industries for which innovation is the basis of competition (Stuart et al., 1999). The importance of signaling technological capabilities is particularly great in a high-tech context, where they are of paramount importance for firm success and survival (Baum and Silverman, 2004).

Similarly, rational ICO investors will prefer to invest in ventures with higher technological capabilities, as the higher value of a more successful company is likely reflected in the value of the token (e.g., Reiff, 2018; Schwartzkopff, 2018). Depending on whether the investor's main motivation is of a more technological nature, a higher value could be reflected in a higher utility offered by the token, because, for example, the venture's project is developed further or in a more advanced way (Brummer, 2018). More often, high returns on investment are cited as the major motivation of ICO investors (e.g., Adkisson, 2018; Cohney et al., 2018; Madeira, 2018). In this case, a higher value might manifest itself in higher dividends or a higher post-ICO valuation of the token in the secondary market, which then enables investors to sell the token to receive a return on their investment.

4.3.3 Signals for technological capabilities in the ICO context

Since the quality of a venture (here: technological capabilities) is often not directly observable, investors must base their investment decision on observable characteristics that signal the venture's underlying quality (Stuart et al., 1999).

Despite the overall paucity of information surrounding ICOs, the technological information available in the ICO context is rich. This is because ventures utilizing DLT are often technology-driven and frequently profile themselves through technological advances. Also, technical information is often more objective, less affected by the greater desire for anonymity, and suits the more technical environment of ICOs.

In the following, I explore three indicators that ventures could use to signal higher technological capabilities.

Patents

Patents are the most commonly used signal for technological capabilities in prior research, which shows that patents (both applications and granted patents) are crucial to acquire entrepreneurial finance (e.g., Baum and Silverman, 2004; Haeussler et al., 2012; Hsu and Ziedonis, 2013). Research also shows that patents are particularly important in early-stage financing (Hoenen et al., 2014).

Patents satisfy the criteria for effective signals: First, they are published publicly and are thus observable. Usually, they are also communicated actively by the venture. If a venture does not mention having a patent, it is not an observable signal to investors (Colombo et al., 2018). Second, they are costly to acquire. In addition to the direct costs (e.g., application, renewal fees), the preparation of patent applications requires a considerable investment of effort and time (Haeussler et al., 2012). In contrast to ventures with higher technological capabilities, those with lower technological capabilities will have to invest more in developing and describing their technical invention in a way that is suitable for a successful patent application. In particular, patents are only granted for inventions that are new and non-obvious. Ventures with higher technological capabilities will have to invest less in applying for a patent that can meet these criteria.

This establishes a separating equilibrium, where only ventures with high technological capabilities apply for patents, thus making the patent an effective signal to communicate a venture's higher technological capabilities to potential investors (Hsu and Ziedonis, 2013; Hoenen et al., 2014). In the ICO context, patents should be a similarly effective signal to reduce information asymmetry between ventures and potential investors.

Technical white paper

The publication of Bitcoin's white paper (Nakamoto, 2008) was a major milestone in the history of blockchain technology and cryptocurrency. Following this example, most ventures publish white papers. A white paper is a document in which a venture provides information it deems necessary to the public and constitute an important component of a venture's ICO campaign (e.g., Cohney et al., 2018; Lielacher, 2017).

While white papers do not follow standard guidelines, one important and common component of a white paper is the technical description of the venture's project and its applications. Investor's guides often recommend careful evaluation of the technical descriptions in a white paper to identify successful ICOs (e.g., Lielacher, 2017; Reiff, 2018). I also interviewed multiple experts and ventures in the domain of ICOs, who suggested that the description of a venture's technology in a white paper is crucial with regard to attracting investors. Specifically, they acknowledged that a white paper is one of the premier outlets for showcasing technological expertise. Similarly, guides for writing white papers recommend ventures include a detailed description of the technology (e.g., Lashkov, 2017; Brummer, 2018).

While potential investors may not be able to understand every technical detail outlined in a white paper, it is reasonable to assume that potential investors in ICOs use the portrayal of technology in the white paper to make inferences about the venture's technical proficiency. Hence, I argue that a technical white paper (sometimes also referred to as a "yellow paper") functions as another signal of a venture's underlying technological capabilities.

A technical white paper is observable because having and distributing a white paper is a de facto standard in ICOs that investors recognize. Also, producing a technical white paper involves considerable cost, which varies for ventures with lower and higher technological capabilities. Describing the highly complex technological background of blockchain technology as well as outlining how the venture is going to build on and extend this technology requires a considerable amount of technological knowledge, effort, and time. This is particularly salient in the ICO context because many ventures are in the early stages of development and often do not have a working project at the time of their ICO (Cohney et al., 2018; Russo and Kharif, 2017). Also, many projects fail to provide technical information in their white paper. I argue that lower quality ventures (i.e., with lower technological capabilities) will find it more costly to produce a technical white paper that includes a detailed account of their own technology with an explanation of the technological infrastructure and its implementation. Instead, they will default to producing a nontechnical white paper. These ventures' white papers might focus on, for example, the venture's team or business model.

This establishes a separating equilibrium in which only ventures with high technological capabilities can produce a technical white paper, making it an effective signal.

High-quality source code

Developments based on blockchain technology (or DLT more generally) occur in the form of programming. Cohney et al. (2018) refer to a venture's source code (i.e., the result of these programming activities) as a core component of the venture and I argue that a venture's source code could be another signal of its technological capabilities.

Most ventures divulge their code online so that the source code (or the lack thereof) is observable. Code is usually published on the platform GitHub (www.github.com), an open-source community platform for programmers. The important role of source code in ICOs is underlined by the fact that most ICO-tracking sites include references to a venture's source code. Also, ventures' communication channels usually reference the source code prominently (e.g., website, white paper, social media). Furthermore, many articles surrounding ICOs (especially investor's guides) highlight the importance of assessing GitHub prior to investing in an ICO (e.g., Bhowmik, 2017; Mulders, 2018).

However, while revealing code may be a de facto standard (Cohney et al., 2018), it is not an effective signal that differentiates ventures with high and low technological capabilities. It is the code's quality that should be the decisive factor. Producing high-quality source code is inherently costly, as it requires considerable amounts of technical expertise. As such, ventures with low technological capabilities will find it significantly more costly, maybe even impossible, to develop high-quality code. In contrast, ventures with high technological capabilities will face lower costs (e.g., time and effort). This constitutes a separating equilibrium in which only ventures with high capabilities develop high-quality code. This, however, gives rise to a related question: How can investors judge the quality of a venture's source code if they lack programming expertise?

Code on GitHub is organized in repositories. Alongside the actual source code, every repository includes aggregate metrics that may be indicative of code's quality without requiring investors to actually read and understand the code. The most commonly used metrics utilize commits (i.e., changes made to the code) (Dabbish et al., 2012; Kalliamvakou et al., 2014; Ray et al., 2014). Using the commit history to infer code quality is established in research in computer sciences. Instead of using the mere number of commits, research uses the number of commits that refer to defect or bug fixes as a direct measure of code quality (e.g., Ray et al., 2014; Syer et al., 2015; Vasilescu, 2015). The number of defect-fixing changes inversely approximates the number of defects in source code. A higher number of fixes corresponds to a lower number of defects, indicating a higher quality of the source code (e.g., Syer et al., 2015).

From a signaling theory perspective, the number of defect-fixing commits is observable. This also applies to investors with little programming expertise; examining the code does not require an understanding of the actual code. A higher number of bug-fixing commits is also differently costly to produce. Ventures with lower technical capabilities will have to invest considerably more time and resources into fixing defects in their code, or will not be able to do so at all. In contrast, high-quality ventures will find it comparatively less demanding to fix defects in their code and will thus commit a higher number of bug fixes, establishing a separating equilibrium.

4.4 Data and variables

4.4.1 Data

A universal database on ICOs does not (yet) exist. As such, the sample used in this study was manually compiled from February to August 2018 and comprises data from multiple sources.

First, CoinSchedule's list of ICOs serves as the basis. CoinSchedule is a comparatively comprehensive and established data source that has been featured in many reputable outlets (e.g., Economist, 2017; Roose, 2017). The data from CoinSchedule were collected in April 2018. At the time of data collection, the list contained a population of 456 unique ICOs that were completed from March

2016 (first entry) until March 2018. Along with the amount raised in the ICO in $, CoinSchedule provides information on the website, sector, and end date of the ICO.

Second, I retrieved additional information on every ICO listed in CoinSchedule from a multitude of other ICO-tracking sites. This included sites such as www.icodrops.com, www.icobench.com, www.coinmarketcap.com, and www.tokenmarket.net. All of these provide information on different ICOs, but no single site contains all the information used in the analysis. I collected additional data from every venture's website, Twitter, and GitHub. I cross-referenced the information provided on the ICO-tracking sites (such as company location) with that provided on the respective venture's homepage and other sites.

Third, I obtained every venture's white paper, mostly from the venture's website or from ICO-tracking pages.

Despite considerable effort, several ICOs had to be excluded. Specifically, some ICOs listed on CoinSchedule were pre-ICOs, which would be followed by the actual ICO at a later point in time (16 observations). Several other observations had to be excluded because of missing data (17 observations). Of these 17 observations, 10 were excluded because I was unable to obtain a white paper. After excluding the above-mentioned observations, the final sample was reduced to 423 ICOs. Notice, however, that this sample can be described as very comprehensive given the limited availability of data on ICOs.

4.4.2 Variables

Dependent variable: amount raised (log.)

The amount of funding raised in the ICO is the dependent variable (in $). This is a commonly used dependent variable in entrepreneurial finance research (e.g., De Clerq and Dimov, 2008; Mollick, 2014). The data are obtained from CoinSchedule. In line with prior research, I use a natural log transformation to account for the skewness of the variable (Anglin et al., 2018; Block et al., 2018b).

Independent variables: signals for technological capabilities

The study explores three potential signals of technological capabilities, which represent the study's independent variables.

Patent (dummy). To capture whether a venture uses patents as a signal, I systematically scanned all venture homepages and white papers for information relating to patents. I also performed an internet search to identify any further information regarding a venture's patents before they conducted the ICO (e.g., interviews, blog posts). If a venture mentions having a patent (application or grant), the variable '*patent (dummy)*' takes a value of 1, and 0 otherwise. If a venture does not mention having a patent, it does not constitute an effective signal since it is not observable to investors (Colombo et al., 2018)

White paper: technical (dummy). Measuring whether a white paper is technical is difficult since there is no established way of operationalization. To minimize the level of subjectivity involved, I had two experienced experts[9] in the ICO domain provide their assessment of whether a white paper is technical or not in addition to my own assessment (‘*white paper: technical (dummy)*’). Specifically, we concluded that a white paper can be considered technical if: (a) the technical implementation of the proposed project is described in detail (e.g., includes architecture, sample code, processes, algorithms, protocols), and (b) if the explanations show the technological expertise of the authors and are not overly superficial. Then, we independently categorized all 423 white papers as technical (= 1) or not (= 0). The inter-rater reliability (kappa) is 0.90, which can be classified as “almost perfect” (Viera and Garrett, 2005). The agreement across all three raters is 94.3 %, 399 out of 423 were coded without disagreement. If the rating was not unanimous, the white paper was coded in line with the majority of ratings (two out of three).

High-quality source code. The variable ‘*GitHub (dummy)*’ captures whether a venture had any source code available on GitHub at the start of the ICO. The variable takes a value of 1 if the venture had at least one commit in a GitHub repository (i.e., revealed any code) and 0 otherwise.

The most commonly used measure of source code quality is the number of defect fixes to a source code (e.g., Ray et al., 2014; Syer et al., 2015; Vasilescu, 2015). Following this research, I use GitHub to measure the number of defect fixes (‘*GitHub: defect fixes*’). Specifically, I first download every venture’s commit history from GitHub (through GitHub’s API), which allows access to all changes made to a venture’s code. I then identified the commits that were issued before the starting date of the ICO to get the most precise reflection of the code that investor’s had available at the time of the ICO. In addition to the date of issuance, each commit includes a brief description. Following Syer et al. (2015), I then mined these descriptions for the keywords “fix(ed/es)”, “bug(s)”, “defect(s)”, and “patch(s/ed/es)” to identify the commits that refer to defect fixes. The variable is included in logged form to account for its high skewness.

Including the *‘GitHub (dummy)’* controls for the fact that ventures without any code on GitHub may be different from those that do reveal their code on GitHub, but that did not commit any defect fixes.

Control variables: characteristics of the ICO campaign

To rule out confounding effects, and to explore additional (potential) determinants of the amount raised in ICOs, the analyses include an extensive list of control variables. Some of the variables may refer to a venture’s capabilities, while others do not.

[9] Both experts have practical knowledge of ICOs. The first expert is an experienced investor and has evaluated multiple ICOs. The second expert works as a consultant in the ICO domain and also has a large experience with regard to evaluating ICOs.

The first set of control variables refers to characteristics of the ICO campaign. These variables are often unique to the ICO context but are inspired by research on crowdfunding, which shows that several entrepreneur-determined characteristics of a campaign can influence the amount raised (e.g., Anglin et al., 2018; Mollick, 2014).

Tokens offered (share). A characteristic unique to ICO campaigns is the relative number of tokens offered for sale. Usually, ventures do not sell all of the tokens issued, electing instead to keep a share of the tokens in the company. An established stream of research argues that entrepreneurs' willingness to invest in their own venture indicates higher commitment and signals higher quality (Busenitz et al., 2005; Leland and Pyle, 1977; Vismara, 2016). In the ICO context, ventures that retain a larger fraction of tokens may signal commitment, while also aligning the interests of owners and employees (who are usually rewarded with tokens) and investors. On the other hand, tokens rarely correspond to equity and most ventures retain full ownership irrespective of the share of tokens offered. Ultimately, it is thus unclear whether and how potential investors will value the share of tokens offered. I thus include the control variable '*tokens offered (share)*', which is scaled continuously from 0 to 1 and is obtained from the venture's white paper, website, or ICO-tracking sites.

Pre-sale (dummy). Research on crowdfunding shows that attracting early-investors is crucial for campaign success (e.g., Colombo et al., 2015; Vismara, 2018). This is in part due to word-of-mouth generated by early investors, but also because they trigger imitating behavior. Often, ICOs conduct a pre-sale (also referred to as "pre-ICO"), in which a usually small share of tokens are sold to early-investors at a discount over a brief period. A pre-sale might lead to an increased amount raised, similar to the crowdfunding context. Therefore, the variable '*pre-sale (dummy)*' captures whether a venture held a pre-sale (= 1) or not (= 0). It should be noted that the amount collected or share of tokens sold in a pre-sale are often not disclosed and are included as part of the official ICO. For example, CoinSchedule only reports the full amount raised in the ICO campaign, including the pre-sale.

Duration (in days). Crowdfunding research frequently includes the campaign's duration as a control variable (e.g., Anglin et al., 2018; Vismara, 2016). Ventures can freely decide how long their ICO should last. Some set very short durations, while others set very long durations. Longer campaigns have the potential to collect higher amounts of funding simply because they run longer. However, previous research shows a strong association between shorter duration and the amount raised and argues that campaigns that reach their goals quicker are more successful (e.g., Courtney et al., 2017; Mollick et al., 2014). Therefore, I control for the '*duration (in days)*', primarily to rule out a confounding influence on the amount raised.

Token type: utility (dummy). It is unclear whether investors in ICOs attribute higher valuations to tokens that propose greater utility or to tokens that position themselves as investments (e.g., by paying dividends or representing equity shares). I include the variable '*token type: utility (dummy)*' to capture whether the token can be characterized as a utility token. Because this information is not available in a standardized way, I compiled data from white papers, ventures' web sites, and ICO-tracking sites. If a venture highlights the utility of its token, the variable is coded as 1. Most often, this is clearly stated in the disclaimer of the venture's white paper. If the investment function is highlighted, the variable takes a value of 0.

Token supply (log.). Ventures can freely determine the absolute number of tokens that will be issued. Some ventures issue trillions of tokens, while others issue less than 10,000. Notice, however, that tokens are divisible so that it is possible to buy a fraction of a single token. From a signaling theory perspective, token supply should not have an impact on the amount of funding received, as the signal is not costly to produce. However, finance research shows that investors are drawn to lottery-type stocks, which are characterized by a low price and a tiny probability of achieving a huge reward (e.g., Eraker and Ready, 2015; Kumar, 2009). Data on the price per token during the ICO, however, is rarely available and crucially depends on the price of Bitcoin or Ether at that time. Instead, a higher token supply is typically related to a lower price and may thus be indicative of lottery-like features. Also, anecdotal evidence suggests that investors frequently compare ICO tokens to Bitcoin in an attempt to find "the next Bitcoin" (Mourdoukoutas, 2018). In this sense, buying a high quantity of cheap tokens with the hope that they reach a similar value to Bitcoin represents a lottery-type payoff. I thus include the variable '*token supply (log.)*', which is obtained from white papers, web sites, or ICO-tracking sites. The variable is transformed by its natural logarithm due to its high skewness.

Ethereum-based (dummy). Ventures can develop their own DLT or build on existing ones. As of 2018, a multitude of DLT platforms exist that ventures can develop applications on and use as their infrastructure (e.g., Ethereum, NEO, Waves). The most common standard to build on is called "Ethereum" (Magas, 2018). Ethereum-based tokens are also referred to as ERC20 ("Ethereum Request for Comment") or ERC223, which is the technical standard they implement. Ethereum was the first platform to popularize and implement "smart contracts" and "dApps" (decentralized applications), which enable the use of Ethereum's blockchain for various applications. Ethereum has since promoted the rapid development of applications (Magas, 2018). Ethereum also defines the rules that certain transactions need to follow to meet and enable greater interoperability between transaction parties in the Ethereum ecosystem. As such, building a token based on Ethereum may signal a higher future utility if investors assume that the Ethereum standard will successfully establish itself as the benchmark for ICOs. The variable '*Ethereum-based (dummy)*' captures whether an ICO builds on Ethereum (= 1) or not (= 0). Data are obtained primarily from ventures' white papers and are aided by information from venture websites and ICO-tracking sites.

Bitcoin price (in 1,000 $). Bitcoin is the initial cryptocurrency and has the highest market capitalization (as of September 2018). Furthermore, Bitcoin is frequently used as the premier method of payment for tokens in ICOs, which often raise funding in Bitcoin (or Ether) instead of $ or €. As such, the amount raised in an ICO is heavily dependent on the value of Bitcoin at the time of the ICO.[10] If a venture collects a given amount of Bitcoin when its price is high, this corresponds to a larger amount raised in $. Moreover, a higher Bitcoin price generally indicates a more positive market sentiment, potentially driving ICO funding up even further. To control for these effects, I include '*Bitcoin's price (in 1,000 $)*' as obtained from www.coinmarketcap.com at the start of the ICO using the daily opening price.

Time dummies. Finally, the market for ICOs is dynamic and rapidly evolving. To rule out any confounding influences that may have developed over time, for example, due to regulatory changes, I create a set of 9 dummy variables that capture time differences on a quarterly basis (from Q1, 2016 until Q1, 2018).

Control variables: venture characteristics

Prior research indicates that a venture's characteristics can influence the amount of funding raised in entrepreneurial finance. They constitute the second set of control variables (e.g., Ahlers et al., 2015; Baum and Silverman, 2004).

Twitter activity. Entrepreneurs increasingly manage personal and business networks online, especially via Twitter (e.g., Fischer and Reuber, 2011; Smith et al., 2017). As such, a venture's activity on Twitter might be important for attracting potential investors. A venture's activity level can be captured by the number of messages ("Tweets") sent on Twitter (Kuppuswamy and Bayus, 2017). Research on crowdfunding shows that updates play a crucial role in attracting funding (e.g., Block et al., 2018b; Kim et al., 2016). Updates signify a venture's intention of reaching out to and transparently communicating with potential investors, thereby reducing information asymmetry and functioning as a signal of venture quality. Similarly, the number of Tweets sent during the ICO campaign can update potential investors on the campaign's progress while also indicating a higher degree of community engagement, thereby reducing information asymmetry (e.g., Benedetti and Kostovestky, 2018). The variable '*Twitter activity*' measures the number of Tweets sent during a venture's ICO campaign, which is manually obtained from ventures' Twitter profiles.

White paper: team (dummy). Prior research shows that a venture's team can be a crucial signal of quality that is important for attracting entrepreneurial finance (e.g., Allison et al., 2017;

[10] The correlation between the price of Bitcoin and Ether was 0.88 in the year 2017 (own calculations using data on daily prices from www.coinmarketcap.com).

Baum and Silverman, 2004). However, given the peculiarities of ICOs in comparison to more traditional funding settings (i.e., higher potential for identity fraud, greater concern for anonymity), the impact of a given venture's team might be less pronounced in ICOs than in more traditional settings. To control for a potential effect on the amount raised, I include the variable '*white paper: team (dummy)*' to capture whether a venture chooses to introduce its team to potential investors in its white paper (= 1) or not (= 0).

White paper: word count (in 1,000). There is considerable heterogeneity with regard to the length of white papers, and it stands to reason that ventures that provide more information in their white paper could be more attractive investments (e.g., Cohney et al., 2018; Moss et al., 2018). However, recent crowdfunding research shows no relationship between the number of words used in investor pitches or descriptions and investment success (Moss et al., 2018; Parhankangas and Renko, 2017). Some research even indicates that fewer words are associated with a higher success rate (Davis et al., 2017; Kim et al., 2016). Kim et al. (2016) indicate that disclosing too much information may backfire when raising funds in open settings. Another explanation is that a lower word count may indicate greater precision (Parhankangas and Renko, 2017), which is generally well-received by potential investors (Davis et al., 2017). To rule out a confounding influence on the amount raised, I include the variable '*white paper: word count (in 1,000)*', which is obtained from assessing all white papers via the software Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2015). LIWC is an established software for the computerized assessment of language and has been applied frequently in crowdfunding research (e.g., Kim et al., 2016; Parhankangas and Renko, 2017).

Location dummies. A venture's location is crucial for attracting finance, such as venture capital (e.g., Stuart and Sorenson, 2003) and even crowdfunding (e.g., Mollick, 2014), albeit to a lesser extent for the latter due to its online context (e.g., Agrawal et al., 2015). Usually, a limited geographic spread is explained by spillovers or industrial clusters that can positively impact a venture's productivity. Recent media coverage suggests that Switzerland is undertaking various efforts to attract DLT ventures (Economist, 2018a) and is actively trying to establish a locational cluster for ventures that are willing to carry out an ICO. To explore a locational effect on the amount of funding raised in ICOs, I thus include dummy variables that capture whether a venture is based in the US, Europe, or the rest of the world (reference group).

Sector dummies. To account for differences in the amount of funding between different sectors or industries, I include a set of dummies derived from CoinSchedule. While all ventures revolve around DLT and thus belong to the knowledge-intensive IT sector, a more fine-grained differentiation may reveal that certain subfields receive higher amounts of funding than others. Specifically, I distinguish between the sectors '*entertainment*' (e.g., gaming, gambling), '*finance*' (e.g., payments, investing), '*infrastructure*' (e.g., data storage, machine learning), and '*others*' (reference group).

4.5 Main analysis: determinants of the amount raised in ICOs

4.5.1 Descriptive analysis

Table 4.1 displays descriptive statistics for the 423 observations included in the analysis.

Dependent variable (amount raised). The 423 ventures in the sample raised total funding of 8.3 \$b. The mean value is 19.6 \$m (mean of the logged variable = 15.99), and the median is 11.8 \$m (median of the logged variable = 16.28). The variable is skewed: The largest ICO in terms of funding collected 320 \$m (log. = 19.58), while the smallest ICO in terms of funding collected 0.02 \$m (log. = 10.08).

Independent variables (signals for technological capabilities). Surprisingly, only 32 ventures (7.6 %) in the sample mentioned having a patent (either pending or granted). Out of these 32 ventures, only 4 mentioned a patent grant, and only 11 provided a more thorough description of the patent's content. Having a technical white paper was more common: Approximately 23 % of the ventures had a technical white paper. Revealing the source code was very common among the ventures, as 66.9 % of the ventures had publicly uploaded source code to GitHub before their ICO. However, there is considerable heterogeneity when it comes to the number of defect fixes that indicate source code quality. While numerous ventures did not commit any defect fixes, the mean is approximately 121 (mean of the logged variable = 1.46), ranging to a maximum of 19,427 (maximum of the logged variable = 9.87).

Table 4.1: Variables and descriptive statistics

Variable	Mean	SD	Min.	Median	Max.	Data source
Dependent variable						
Amount raised (log.)	15.99	1.48	10.08	16.28	19.58	CoinSchedule
Independent variables: signals for technological capabilities						
Patent (dummy)	0.08	-	0.00	0.00	1.00	Various[a]
White paper: technical (dummy)	0.23	-	0.00	0.00	1.00	Expert rating
GitHub (dummy)	0.67	-	0.00	1.00	1.00	GitHub
GitHub: defect fixes (log.)	1.46	2.04	0.00	0.00	9.87	GitHub
Control variables: characteristics of the ICO campaign						
Tokens offered (share)	0.56	0.21	0.04	0.55	1.00	Various[b]
Pre-sale (dummy)	0.65	0.48	0.00	1.00	1.00	Various[b]
Duration (in days)	24.63	21.14	1.00	28.00	172.00	Various[b]
Token type: utility (dummy)	0.83	0.37	0.00	1.00	1.00	Various[b]
Token supply (log.)	19.04	2.29	7.13	18.92	29.93	Various[b]
Ethereum-based (dummy)	0.78	-	0.00	1.00	1.00	Various[b]
Bitcoin price (in 1,000 $)	7.24	5.01	0.41	6.11	19.48	Coinmarketcap
Q1 2016 (dummy)	0.01	-	0.00	0.00	1.00	CoinSchedule
Q2 2016 (dummy)	0.01	-	0.00	0.00	1.00	CoinSchedule
Q3 2016 (dummy)	0.03	-	0.00	0.00	1.00	CoinSchedule
Q4 2016 (dummy)	0.03	-	0.00	0.00	1.00	CoinSchedule
Q1 2017 (dummy)	0.03	-	0.00	0.00	1.00	CoinSchedule
Q2 2017 (dummy)	0.15	-	0.00	0.00	1.00	CoinSchedule
Q3 2017 (dummy)	0.24	-	0.00	0.00	1.00	CoinSchedule
Q4 2017 (dummy)	0.25	-	0.00	0.00	1.00	CoinSchedule
Q1 2018 (dummy, ref.)	0.25	-	0.00	0.00	1.00	CoinSchedule
Control variables: venture characteristics						
Twitter activity	37.42	39.92	0.00	29.00	347.00	Twitter
White paper: team (dummy)	0.56	-	0.00	1.00	1.00	White paper
White paper: word count (in 1,000)	8.19	5.00	0.42	7.09	32.64	White paper
Location: US (dummy)	0.22	-	0.00	0.00	1.00	Various[b]
Location: EU (dummy)	0.35	-	0.00	0.00	1.00	Various[b]
Location: other (dummy, ref.)	0.43	-	0.00	0.00	1.00	Various[b]
Sector: entertainment (dummy)	0.16	-	0.00	0.00	1.00	CoinSchedule
Sector: finance (dummy)	0.40	-	0.00	0.00	1.00	CoinSchedule
Sector: infrastructure (dummy)	0.27	-	0.00	0.00	1.00	CoinSchedule
Sector: other (dummy, ref.)	0.17	-	0.00	0.00	1.00	CoinSchedule

Notes: N = 423 ICOs. [a] = collected from white papers, venture websites, and other venture communication (e.g., interviews, blog posts). [b] = collected from ICO-tracking sites (e.g., www.icodrops.com, www.coinbench.com, www.tokenmarket.com), venture websites, and white papers.

Control variables (characteristics of the ICO campaign). On average, ventures offered 56 % of the total amount of tokens in their ICO. While some ventures offered as little as 4 %, others offered 100 %. Pre-sales were common, as 65 % of the ventures chose to offer some tokens to early investors before the actual ICO. The average ICO duration was 25 days, ranging from 1 to 172 days. Utility tokens were by far the most common token type (83 %). Only 17 % were security tokens that offered investors financial benefits. The average number of tokens issued is 25.3 b (mean of the logged variable = 19.04), while the median is 165 b (median of the logged variable = 18.92). The number of tokens issued ranged from 1,250 tokens to a maximum of 10 trillion tokens. 78 % of the ICOs were Ethereum-based. The average Bitcoin price at the start of the ICOs in the sample was 7,239 $. However, there is considerable variation. The Bitcoin price ranged from 413 $ on March 21st, 2016 up to a price of 19,476 $ on December 17th, 2017. Finally, the time dummies reflect the dynamics of the ICO market pictured in Figure 4.1. 74 % of the ICOs occurred from July 2017 until March 2018.

Control variables (venture characteristics). Ventures' Twitter activity varied considerably. While some ventures did not send any Tweets during their ICO campaign, the most active venture sent 347 Tweets. 56 % of the ventures introduced the venture team in their white paper. Conversely, 44 % of the ventures did not refer to their team at all. The average length of all white papers is 8,190 words. The shortest white paper contained 416 words, while the longest was comprised of 32,640 words. The sample's ventures were dispersed globally: While 22 % of them were US-based, 35 % were located in Europe, and 43 % were located in the rest of the world. The latter category mostly refers to Asian countries, such as China, Hong Kong, and Singapore. Finally, 16% of the ventures belonged to the entertainment sector, while 27 % were related to infrastructure. The largest group of ventures (40 %) belonged to the finance sector.

Table 4.2 displays the correlations and variance inflation factors. While there are some significant correlations due to the sample size, the variance inflation factors indicate that multicollinearity should not affect the results severely.

Table 4.2: Correlations and variance inflation factors (VIFs)

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**VIF**
Dependent variable																				
(1) Amount raised (log.)																				1.83
Independent variables: signals for technological capabilities																				
(2) Patent (dummy)	0.10																			1.08
(3) WP: technical (dummy)	0.16*	-0.05																		1.50
(4) GitHub (dummy)	0.13*	0.03	0.12*																	1.52
(5) GitHub: defect fixes (log.)	0.15*	-0.10*	0.22*	0.50*																1.60
Control variables: characteristics of the ICO campaign																				
(6) Tokens offered (share)	-0.26*	-0.04	-0.14*	-0.01	0.02															1.30
(7) Pre-sale (dummy)	0.23*	0.12*	0.00	0.07	-0.08	-0.19*														1.36
(8) Duration (in days)	-0.27*	-0.05	-0.06	-0.19*	-0.13*	0.16*	-0.03													1.59
(9) Token type: utility (dummy)	0.14*	0.10*	0.08	0.13*	0.08	-0.13*	0.09	-0.12*												1.17
(10) Token supply (log.)	0.40*	0.12*	0.04	0.01	-0.02	-0.35*	0.20*	-0.18*	0.23*											1.47
(11) Ethereum-based (dummy)	0.31*	0.05	-0.14*	0.18*	-0.01	-0.14*	0.25*	-0.18*	0.12*	0.15*										1.49
(12) Bitcoin price (in 1,000 $)	0.37*	0.12*	-0.01	0.11*	-0.07	-0.30*	0.38*	-0.05	0.17*	0.31*	0.34*									5.37
Control variables: venture characteristics																				
(13) Twitter activity	0.01	-0.06	-0.07	-0.09	0.00	0.07	0.01	0.40*	-0.03	0.05	-0.04	-0.04								1.30
(14) WP: team (dummy)	0.17*	0.11*	-0.35*	-0.01	-0.18*	-0.08	0.21*	-0.07	0.11*	0.20*	0.37*	0.31*	0.00							1.63
(15) WP: word count (in 1,000)	0.33*	0.12*	0.18*	0.14*	0.03	-0.13*	0.21*	-0.12*	0.11*	0.22*	0.16*	0.30*	0.02	0.28*						1.38
(16) Location: US (dummy)	0.11*	0.09	0.10*	-0.03	0.04	-0.09	-0.07	0.00	0.13*	0.06	0.08	-0.01	-0.01	-0.04	-0.01					1.30
(17) Location: EU (dummy)	-0.07	-0.10*	-0.02	0.02	0.02	0.16*	0.02	0.05	-0.13*	-0.11*	-0.04	-0.03	0.07	0.00	0.02	-0.39*				1.26
(18) Sector: entertainment (dummy)	-0.15*	-0.03	-0.15*	-0.09	-0.06	0.08	-0.07	0.05	0.02	-0.06	0.05	-0.12*	-0.01	0.07	-0.12	0.02	0.00			1.78
(19) Sector: finance (dummy)	0.08	-0.05	-0.07	-0.05	-0.06	0.00	0.03	0.04	-0.12*	-0.03	0.08	0.08	0.05	0.09	0.08	-0.13*	0.03	-0.36*		2.19
(20) Sector: infrastructure (dummy)	-0.01	0.03	0.24*	0.07	0.20*	-0.06	-0.09	-0.08	0.08	0.03	-0.21*	-0.07	-0.05	-0.18*	-0.03	0.10*	-0.03	-0.27*	-0.50*	2.14

Notes: N = 423 ICOs. WP = White paper. Pearson correlation coefficients with significance levels * $p < 0.05$. VIFs estimated based on Model 5 of Table 4.3 (without robust standard errors).

4.5.2 Multivariate analysis

Table 4.3 presents the results of an OLS regression analysis with '*amount raised (log.)*' as the dependent variable. A Breusch-Pagan test indicates that the error terms may be affected by heteroscedasticity. Therefore, all models are estimated with heteroscedasticity-robust standard errors. Each model includes all 423 observations as well as the full set of control variables, including time dummies. The signals for technological capabilities are entered stepwise in Models 1 to 4, and jointly in Model 5. The following explanations refer to the full Model 5. With an R^2 (adjusted) of 0.415, the model fit is considerable.

Results pertaining to the independent variables

Model 5 (Table 4.3) shows that '*patent (dummy)*' does not have a significant influence on the amount raised. While patents are the most common signal of technological capabilities in previous entrepreneurial finance research, they do not seem to constitute an effective signal in the context of ICOs.

However, having a technical white paper strongly influences the amount raised. The coefficient of '*white paper: technical (dummy)*' is significant ($p < 0.01$) and positive, indicating that ventures with a technical white paper are able to raise more funding than those without. Hence, investors might interpret a technical white paper as a strong predictor of a venture's underlying technological capabilities.

'*GitHub (dummy)*' is insignificant, indicating that revealing code on GitHub does not significantly influence the amount of funding raised. Following the logic of signaling theory, this is unsurprising, as revealing the code does not involve a significant cost if potential investors are unable to differentiate between codes of high versus low quality. In contrast, source code quality has a significant impact on the amount of funding raised. The effect of '*GitHub: defect fixes (log.)*' is highly significant ($p < 0.01$) and positive, indicating that an increase in the number of defect fixes corresponds to an increase in the amount raised. This finding suggests that investors seem to consider the venture's source code quality in their investment decisions.

Results pertaining to the control variables

A relation exists between ICO duration and the amount raised ($p < 0.01$). This finding is in line with crowdfunding research that shows a similar association between shorter durations and campaign success (e.g., Courtney et al., 2017; Mollick, 2014). While the finding may seem paradoxical at first, several ICOs managed to reach their funding goals within a matter of hours. These ICOs were often surrounded by a considerable amount of hype (Benedetti and Kostovetsky, 2018).

In addition, ICOs that issued a larger number of tokens reached higher valuations ($p < 0.01$). This finding is surprising, as the number of tokens sold can be freely decided upon by the venture and should thus not infer any reference to its underlying quality. One explanation might be that tokens with higher supply, while controlling for a variety of factors, indeed exhibit lottery-like characteristics and are therefore more attractive investments (Eraker and Ready, 2015; Kumar, 2009).

While differences between utility and security tokens do not seem to influence the amount raised, ventures that build on Ethereum achieve higher valuations than those building their own DLT or drawing on a different standard ($p < 0.01$). This indicates that investors currently value the Ethereum-standard. The development and emergence of standards draw interesting parallels to the literature on competition between platforms, and network externalities more generally, which is an important topic in research on the adoption of innovations (e.g., Boudreau, 2010; Rochet and Tirole, 2003). This result is important, as choosing the optimal standard to build on is a crucial decision that ventures must make in their early stages of development.

The results further indicate that a higher level of Twitter activity during the ICO is associated with a greater amount of funding raised ($p < 0.05$). Related to crowdfunding research, which highlights the crucial role of updates to attain funding (e.g., Block et al., 2018b; Kim et al., 2016), a higher activity level in communicating with potential investors might function as a quality signal in the ICO context.

Additionally, the length of the white paper has a positive influence on the amount of funding raised ($p < 0.01$). While research on crowdfunding indicates that investors value more precise venture communications (e.g., Davis et al., 2017; Kim et al., 2016), investors in the ICO context seem to prefer larger quantities of information disclosed. One explanation might be the considerable amount of information asymmetry present in the ICO context so that investors value everything that is disclosed. Also, very short white papers tend to be superficial.

Finally, ventures located in the US achieve higher valuations than those in other countries ($p < 0.1$). This is a very interesting finding, especially given Switzerland’s recent efforts to establish a cluster for DLT ventures (Economist, 2018a). So far, these attempts do not seem to be reflected in higher investor valuations.

Table 4.3: OLS regression analysis on the determinants of the amount raised in ICOs

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*
Control variables: characteristics of the ICO campaign										
Tokens offered (share)	-0.299	(0.346)	-0.180	(0.337)	-0.312	(0.349)	-0.337	(0.338)	-0.216	(0.331)
Pre-sale (dummy)	0.066	(0.127)	0.045	(0.126)	0.064	(0.126)	0.078	(0.125)	0.058	(0.125)
Duration (in days)	-0.012	(0.003)***	-0.011	(0.003)***	-0.011	(0.003)***	-0.010	(0.003)***	-0.010	(0.003)***
Token type: utility (dummy)	-0.094	(0.190)	-0.128	(0.189)	-0.106	(0.188)	-0.147	(0.183)	-0.165	(0.182)
Token supply (log.)	0.151	(0.030)***	0.151	(0.030)***	0.152	(0.030)***	0.152	(0.028)***	0.148	(0.028)***
Ethereum-based (dummy)	0.453	(0.184)**	0.476	(0.177)***	0.434	(0.181)**	0.408	(0.178)**	0.464	(0.172)***
Bitcoin price (in 1,000 $)	0.028	(0.024)	0.027	(0.023)	0.027	(0.024)	0.024	(0.024)	0.024	(0.023)
Control variables: venture characteristics										
Twitter activity	0.004	(0.002)**	0.004	(0.002)**	0.004	(0.002)**	0.004	(0.002)**	0.004	(0.002)**
White paper: team (dummy)	-0.223	(0.128)*	-0.045	(0.142)	-0.213	(0.130)	-0.139	(0.130)	0.008	(0.143)
White paper: word count (in 1,000)	0.050	(0.010)***	0.038	(0.010)***	0.049	(0.010)***	0.046	(0.010)***	0.036	(0.010)***
Location: US (dummy)	0.346	(0.150)**	0.292	(0.149)*	0.351	(0.149)**	0.331	(0.145)**	0.265	(0.145)*
Location: EU (dummy)	-0.004	(0.133)	-0.030	(0.132)	-0.005	(0.132)	-0.024	(0.130)	-0.043	(0.130)
Sector: entertainment (dummy)	-0.195	(0.209)	-0.179	(0.207)	-0.181	(0.209)	-0.213	(0.204)	-0.224	(0.207)
Sector: finance (dummy)	0.135	(0.172)	0.121	(0.170)	0.145	(0.173)	0.101	(0.171)	0.071	(0.172)
Sector: infrastructure (dummy)	0.116	(0.184)	0.051	(0.184)	0.117	(0.184)	0.016	(0.185)	-0.055	(0.184)
Independent variables: signals for technological capabilities										
Patent (dummy)	-0.008	(0.144)							0.134	(0.142)
White paper: technical (dummy)			0.525	(0.159)***					0.476	(0.158)***
GitHub (dummy)					0.097	(0.128)			-0.189	(0.140)
GitHub: defect fixes (log.)							0.114	(0.028)***	0.128	(0.031)***
Time dummies (quarters)	Yes		Yes		Yes		Yes		Yes	
R^2 (R^2 adjusted)	0.416	(0.381)	0.432	(0.398)	0.417	(0.382)	0.437	(0.404)	0.453	(0.415)
Observations (ICOs)	423		423		423		423		423	

Notes: Dependent variable = amount raised (log.). N = 423 ICOs. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models include heteroscedasticity-robust standard errors. The maximum variance inflation factor in Model 5 is 5.37 (‘*Bitcoin price (in 1,000 $)*’). The VIFs are below 2.50 for all other variables, as reported in detail in Table 4.2.

4.6 Robustness checks and further analyses

4.6.1 Alternative estimation techniques and additional control variables

GLM and robust regression

An assessment of the residuals obtained from the main model (Model 5, Table 4.3) via a QQ plot indicates that the error terms are approximately normally distributed. However, a Shapiro-Wilk test for normality indicates that the residuals deviate from a normal distribution. GLM is a generalization of linear regression that allows for dependent variables that have an error distribution other than a normal distribution and are estimated using maximum likelihood estimation. GLM models have been used in recent crowdfunding research to assess the amount of funding raised (Anglin et al., 2018). The results of the GLM model are displayed in Model 1 (Table 4.4) and do not deviate from the main results reported in Model 5 (Table 4.3).

Robust regressions are another set of estimation techniques that can be more efficient than least-squares estimators in the presence of residuals that are not normally distributed. They also account for a potential distortion caused by outliers (Li, 1985). I perform a robust regression in STATA 15 using the command '*rreg*'. This estimation procedure initially removes high-leverage outliers based on Cook's distance (no observations were removed in this sample), before using an iterative maximum likelihood-type estimator (M-estimator) with a weighting procedure, in which larger residuals receive lower weightings than smaller residues (Li, 1985). The results (Model 2, Table 4.4) further underline the robustness of the main analysis.

Controlling for the fundraising goal

Research in crowdfunding frequently uses the fundraising goal as an additional control variable (e.g., Ahlers et al., 2015; Mollick, 2014). A lower fundraising goal might stop the fundraising process earlier, leading to lower amounts raised, irrespective of the venture's quality. However, capturing the fundraising goal is subject to limitations in the ICO context. In particular, not every ICO has a fundraising goal. Some ICOs simply set a period of time to raise as much as possible or set a dynamic funding goal that can change during the ICO (Madeira, 2018).

Irrespective of this limitation, I collected data on fundraising goals from icodrops.com, which provides data on fundraising goals in $. I was able to identify a fundraising goal for 238 ICOs (56.2 %). Model 3 (Table 4.4) includes the fundraising goal in logged form as another control variable. A higher fundraising goal is indeed associated with a higher amount raised. While '*patent (dummy)*' remains insignificant, '*GitHub: defect fixes (log.)*' remains significant. However, '*white paper: technical (dummy)*' loses significance and becomes insignificant. Additionally, '*GitHub (dummy)*' gains significance. However, these changes in significance may be driven by the strong reduction of the sample (N = 238).

Model 4 (Table 4.4) includes a corresponding dummy variable that captures whether the venture had a fundraising goal (= 1) or not (= 0). Here, '*white paper: technical (dummy)*' remains significant ($p < 0.05$), while '*GitHub (dummy)*' loses significance in comparison to Model 3.

4.6.2 Assessing the robustness of the independent variables

The effect of 'white paper: technical (dummy)'

In addition to operationalizing whether a white paper is technical through expert ratings, I capture a technical focus of a white paper by quantifying the number of pages in the paper that refer to the venture's technology.

I argue that a white paper has a technical focus if more than 50 % of the pages concern technology. A page is considered technical if it refers to (a) a venture's technology and its components (e.g., protocol, code, algorithm), (b) technical architecture and ecosystem, or (c) token specifics (not token sale or allocation). These criteria were identified in discussion with two experts (cf. Section 5.2.2) and after scanning multiple white papers with regard to potential technical content. I, along with two scientific research assistants with background knowledge on ICOs quantified the number of pages that refer to technology. If the number of technical pages (rounded to full pages) divided by the number of a white paper's total pages (excluding cover page, table of content, and disclaimer) was more than 50 %, the white paper was coded as 1 for having a technical focus, and 0 otherwise ('*WP: technical focus (dummy)*'). The inter-rater reliability (kappa) across all three raters is 0.89. The agreement across all three raters is 94.1 % percent, and classifications that were not unanimous were excluded and coded according to which rating 2 out of 3 raters assigned.

Adding the variables to the main analysis (Model 1, Table 4.5) indicates that the effect on the amount raised is equally positive and highly significant ($p < 0.01$).

As an additional robustness check, I exclude white papers where the rating across all three raters was not unanimous in subsequent models. Model 2 (Table 4.5) concerns the variable '*white paper: technical (dummy)*' and only includes those white papers where the coding across all three raters was the same. The effects remains significant ($p < 0.05$). Model 3 (Table 4.5) concerns the variable '*white paper: technical focus (dummy)*' includes only those where the three raters unanimously identified more than 50 % of the pages as technical. Again, the results underline the robustness of the main effects ($p < 0.01$). The results also remain robust if only two out of three raters are considered for any of the variables (not reported).

The effect of 'GitHub: defect fixes (log.)'

Not all ventures that revealed their source code conducted defect fixes. Ventures with code on GitHub that have no defect fixes might be different from ventures that have no code (and hence have no defect fixes). I include the variable '*GitHub (dummy)*' to control for these differences. To rule out potential multicollinearity biases of the effect of '*GitHub: defect fixes (log.)*', I reduce the sample to ventures that actually had code on GitHub. This reduces the sample to 283 and makes '*GitHub (dummy)*' obsolete. The results are portrayed in Model 4 (Table 4.5) and underline the robustness of the main effects.

Defect fixes are a subgroup of total commits. The number of commits reflects a venture's activity in terms of its source code. Previous research has associated a higher activity with higher code quality (e.g., Dabbish et al., 2012). While the number of defect fixes is a better proxy of code quality, the number of commits is easier for the average investor to observe, as it is directly summarized on each repository's page. Indeed, ICO investment guides specifically advise investors to assess the number of commits to infer the source code's quality when evaluating ICOs (e.g., Bhowmik, 2017; Mulders, 2018). As a robustness check, Model 5 (Table 4.5) uses '*GitHub: commits (log.)*' (i.e., the number of commits a venture's code had on GitHub prior to the ICO) instead of '*GitHub defect fixes (log.)*'. The results indicate a positive and highly significant ($p < 0.01$) influence and suggest that the number of commits may serve as another signal of code quality in the ICO context.

Third-party endorsements to capture code quality

Previous research shows that third-party endorsements can reduce information asymmetry in the investor-investee relationship (e.g., Colombo et al., 2018; Courtney et al., 2017; Stuart et al., 1999). Potential investors are influenced by third-party evaluations if these third parties are better able to discern quality under conditions of uncertainty, for example, because they are experts in a given field (Stuart et al., 1999). Here, third-party endorsements might help to inform investors about the code's quality.

GitHub allows any individual to create a personal copy of code that they can modify. These changes can then be submitted back to the original project through a so-called "pull request". The original code's owners can then decide to accept, modify, or decline the proposed change. Pull requests by third parties thus resemble regular commits and may similarly indicate a higher code quality (e.g., Dabbish et al., 2012; Kalliamvakou et al., 2014). Also, a pull request signifies a commitment by a third party and involves a considerable investment of time and effort (e.g., Dabbish et al., 2012). I argue that pull requests can be interpreted as endorsements because third parties will only work on code that they feel is worth their contribution.

Pull requests fulfill the criteria of effective signals from the endorser's perspective. They are observable because they are publicly displayed on the user's profile. They also incur varying costs because endorsers who submit low-quality pull requests will suffer a loss in reputation. In fact, previous research suggests that there is a high awareness of being observed by peers on GitHub, leading to performance pressure (Dabbish et al., 2012). Relatedly, the track record of commits and pull requests is frequently assessed to infer individuals' coding abilities, activities, and skills. This information is then used, for example, by recruiters when making hiring decisions (e.g., Dabbish et al., 2012; Marlow and Dabbish, 2013). Also, it is not possible to delete pull requests.

To capture the number of pull requests, I retrieved all pull requests that were issued to a venture's source code before the venture's ICO. The variable '*GitHub: pull requests (log.)*' is included in Model 6 (Table 4.5). The results indicate that the number of pull requests has a positive and significant ($p < 0.01$) influence on the amount raised, suggesting that potential investors may be able to effectively discern a given code's quality based on these expert contributions.

4.7 Discussion and conclusion

4.7.1 Discussion of the main results

Patents do not seem to constitute an effective signal in the ICO context. This finding is surprising and in contrast to prior research in entrepreneurial finance (e.g., Baum and Silverman, 2004; Hsu and Ziedonis, 2013).

An explanation might be that patents are of limited usability for DLT and blockchain ventures because code (and software) is not patentable in various jurisdictions in general (EPO, 2018). In these jurisdictions, only supporting technologies or very specialized elements of code would be patentable. Closely connected, most blockchain ventures reveal their code freely on GitHub. Because patents require a technological invention that is previously undisclosed, they cannot be obtained if the code is already revealed. Another explanation might be that most ventures are in such early stages that they may not yet have technology advanced enough to be patented (Kaal and Dell'Erba, 2018; Russo and Kharif, 2017). Also, the results indicate that ICO ventures may not consider patents to be an important part of their strategy when raising funds because patents are used so rarely by these ventures. A final explanation refers to the receiver's ability to interpret and then act upon the signal (Connelly et al., 2011). Because patents may not be as suitable in the ICO context, investors may not be overly familiar with the concept of patents. In contrast, venture capitalists and business angels pay a lot of attention to patents and are familiar with them (Block et al., 2014).

Table 4.4: Robustness checks using different estimation techniques and additional control variables

	Model 1		Model 2		Model 3		Model 4	
Description	Estimation: Generalized linear model (GLM)		Estimation: Robust regression		Additional control variable: 'Fundraising goal (log.)'		Additional control variable: 'Fundraising goal (dummy)'	
Variable	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*
Control variables: characteristics of the ICO campaign								
Tokens offered (share)	-0.216	(0.321)	-0.157	(0.270)	0.279	(0.395)	-0.074	(0.324)
Pre-sale (dummy)	0.058	(0.121)	0.032	(0.123)	0.296	(0.124)**	0.063	(0.124)
Duration (in days)	-0.010	(0.003)***	-0.012	(0.003)***	-0.008	(0.003)**	-0.008	(0.003)***
Token type: utility (dummy)	-0.165	(0.176)	-0.213	(0.146)	0.059	(0.195)	-0.209	(0.175)
Token supply (log.)	0.148	(0.027)***	0.150	(0.026)***	0.118	(0.025)***	0.138	(0.028)***
Ethereum-based (dummy)	0.464	(0.166)***	0.465	(0.146)***	-0.134	(0.131)	0.439	(0.166)***
Bitcoin price (in 1,000 $)	0.024	(0.023)	0.020	(0.023)	-0.012	(0.021)	0.010	(0.023)
Fundraising goal (log.)					0.654	(0.071)***		
Fundraising goal (dummy)							0.734	(0.174)***
Control variables: venture characteristics								
Twitter activity	0.004	(0.002)**	0.003	(0.001)**	0.001	(0.002)	0.003	(0.002)
WP: team (dummy)	0.008	(0.139)	-0.073	(0.130)	-0.211	(0.097)**	-0.012	(0.135)
WP: word count (in 1,000)	0.036	(0.010)***	0.032	(0.012)***	0.013	(0.011)	0.034	(0.010)***
Location: US (dummy)	0.265	(0.140)*	0.221	(0.139)	0.126	(0.121)	0.258	(0.145)*
Location: EU (dummy)	-0.043	(0.126)	-0.060	(0.118)	0.005	(0.113)	-0.018	(0.126)
Sector: entertainment (dummy)	-0.224	(0.200)	-0.340	(0.183)*	-0.394	(0.212)*	-0.196	(0.208)
Sector: finance (dummy)	0.071	(0.167)	0.046	(0.152)	0.073	(0.139)	0.125	(0.168)
Sector: infrastructure (dummy)	-0.055	(0.178)	-0.037	(0.167)	0.107	(0.161)	-0.041	(0.179)
Independent variables: signals for technological capabilities								
Patent (dummy)	0.134	(0.137)	0.057	(0.199)	0.002	(0.135)	0.154	(0.148)
WP: technical (dummy)	0.476	(0.153)***	0.329	(0.145)**	0.147	(0.112)	0.388	(0.154)**
GitHub (dummy)	-0.189	(0.135)	-0.157	(0.132)	-0.357	(0.123)***	-0.232	(0.133)*
GitHub: defect fixes (log.)	0.128	(0.030)***	0.096	(0.031)***	0.071	(0.032)**	0.122	(0.030)***
Time dummies (quarters)	Yes		Yes		Yes		Yes	
Chi^2	726.267	***	-		-		-	
R^2 (R^2 adjusted)	-		0.470	(0.434)	0.549	(0.501)	0.478	(0.441)
Observations (ICOs)	423		423		238		423	

Notes: Dependent variable = amount raised (log.). WP = White paper. * p < 0.10, ** p < 0.05, *** p < 0.01. All models except for Model 2 include heteroscedasticity-robust standard errors.

Table 4.5: Robustness checks pertaining to the independent variables

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**	
Description	Alternative measure: WP: technical focus (pages, dummy)		Reduced sample: Excluding unanimous ratings (#1)		Reduced sample: Excluding unanimous ratings (#2)		Subsample: ICOs with at least one commit		Alternative proxy: 'GitHub: commits (log.)'		Alternative proxy: 'GitHub: pull requests (log.)'	
Variable	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*	*Coeff.*	*(SE)*
Control variables: characteristics of the ICO campaign												
Tokens offered (share)	-0.206	(0.332)	-0.186	(0.335)	-0.292	(0.332)	0.568	(0.429)	-0.232	(0.337)	-0.219	(0.339)
Pre-sale (dummy)	0.089	(0.124)	0.059	(0.127)	0.082	(0.131)	-0.009	(0.155)	0.048	(0.126)	0.039	(0.127)
Duration (in days)	-0.009	(0.003)***	-0.011	(0.003)***	-0.009	(0.003)***	-0.009	(0.004)**	-0.009	(0.003)***	-0.010	(0.003)***
Token type: utility (dummy)	-0.156	(0.181)	-0.125	(0.184)	-0.089	(0.188)	-0.390	(0.203)*	-0.176	(0.183)	-0.151	(0.186)
Token supply (log.)	0.152	(0.029)***	0.150	(0.030)***	0.152	(0.029)***	0.163	(0.035)***	0.153	(0.029)***	0.148	(0.029)***
Ethereum-based (dummy)	0.493	(0.174)***	0.432	(0.174)**	0.464	(0.184)**	0.328	(0.194)*	0.413	(0.172)**	0.430	(0.175)**
Bitcoin price (in 1,000 $)	0.029	(0.023)	0.026	(0.024)	0.029	(0.024)	0.027	(0.031)	0.022	(0.023)	0.026	(0.024)
Control variables: venture characteristics												
Twitter activity	0.004	(0.002)**	0.005	(0.002)**	0.004	(0.002)**	0.001	(0.003)	0.004	(0.002)**	0.004	(0.002)**
WP: team (dummy)	0.045	(0.146)	-0.002	(0.155)	0.063	(0.149)	-0.154	(0.162)	0.005	(0.143)	-0.053	(0.143)
WP: word count (in 1,000)	0.039	(0.010)***	0.039	(0.010)***	0.037	(0.010)***	0.032	(0.012)***	0.035	(0.010)***	0.039	(0.010)***
Location: US (dummy)	0.278	(0.145)*	0.340	(0.153)**	0.252	(0.149)*	0.320	(0.159)**	0.297	(0.146)**	0.272	(0.147)*
Location: EU (dummy)	-0.016	(0.129)	-0.031	(0.133)	0.006	(0.133)	-0.140	(0.154)	-0.033	(0.131)	-0.034	(0.130)
Sector: entertainment (dummy)	-0.221	(0.206)	-0.098	(0.211)	-0.266	(0.214)	-0.213	(0.258)	-0.174	(0.205)	-0.234	(0.206)
Sector: finance (dummy)	0.080	(0.172)	0.107	(0.178)	0.031	(0.178)	-0.091	(0.197)	0.120	(0.169)	0.054	(0.172)
Sector: infrastructure (dummy)	-0.057	(0.183)	-0.039	(0.190)	-0.084	(0.192)	-0.092	(0.197)	-0.009	(0.186)	-0.036	(0.184)
Independent variables: signals for technological capabilities												
Patent (dummy)	0.101	(0.143)	0.200	(0.139)	0.096	(0.146)	0.090	(0.187)	0.078	(0.141)	0.075	(0.140)
WP: technical (dummy)	-		0.427	(0.171)**	-		0.468	(0.172)***	0.481	(0.158)***	0.438	(0.161)***
WP: technical focus (dummy)	0.536	(0.163)***	-		0.606	(0.178)***	-		-		-	
GitHub (dummy)	-0.197	(0.140)	-0.202	(0.144)	-0.199	(0.142)	-		-		-	
GitHub: defect fixes (log.)	0.114	(0.031)***	0.131	(0.032)***	0.131	(0.032)***	0.117	(0.031)***	-		-	
GitHub: commits (log.)	-		-		-		-		0.066	(0.023)***	-	
GitHub: pull requests (log.)	-		-		-		-		-		0.133	(0.037)***
Time dummies (quarters)	Yes		Yes		Yes		Yes		Yes		Yes	
R2 (R2 adjusted)	0.455	(0.418)	0.448	(0.407)	0.446	(0.406)	0.431	(0.373)	0.443	(0.407)	0.447	(0.409)
Observations (ICOs)	423		399		398		283		423		423	

Notes: Dependent variable = amount raised (log.). WP = White paper. * p < 0.10, ** p < 0.05, *** p < 0.01. All models include heteroscedasticity-robust standard errors.

A technical white paper may be an effective signal in ICOs in contrast to patents. Interestingly, both patents and technical white papers constitute a detailed description of a venture's technological efforts. However, while they are similar in terms of general content, a technical white paper is less restrictive with respect to legal necessities (e.g., paying fees, involving a patent lawyer, referencing prior knowledge). Most importantly, however, patents require that an invention is previously undisclosed, while a venture can publish a technical white paper to demonstrate its technological capabilities even if it has already revealed its code. To some extent, technical white papers may constitute a substitute for patents in the specific context of ICOs.

However, the link between a technical white paper and higher technological capabilities is not completely straightforward. Research in crowdfunding finds that ventures that are able to communicate as precisely as possible raise more funding (e.g., Davis et al., 2017; Kim et al., 2016; Parhankangas and Renko, 2017). This may be reflected in technical language, but it may also lie in being able to describe a highly technical problem in a very nontechnical and understandable way so that those who have particularly high technological capabilities are actually able to communicate in a nontechnical way. Also, it may be that ventures with low technological capabilities try to hide behind technical language (Jafery, 2018). However, the results do indicate that investors seem to be persuaded by a more technical appearance of a white paper.

Finally, a high-quality code is associated with an increased amount of funding. The source code is a relatively objective characteristic that most investor's guides suggest investors assess when making an informed decision about investing in ICOs (e.g., Bhowmik, 2017; Mulders, 2018). While most investors may not understand the detailed technicalities of source code, GitHub present multiple aggregate metrics that seem to help investors refer to the venture's underlying technological capabilities.

4.7.2 Implications

Implications for theory

This study extends the literature on entrepreneurial finance by introducing ICOs as a new mechanism for ventures to raise capital. While raising capital in an ICO shares similarities with crowdfunding (e.g., Ahlers et al., 2015; Mollick, 2014), this study highlights the importance of different signals of a venture's underlying technological capabilities, which previous research has either analyzed via patents or not at all. Gaining an initial understanding of the dynamics of ICOs is crucial for entrepreneurial finance research and this study can thus serve as the basis for future, more nuanced studies as the field develops. In addition, this study contributes to the entrepreneurial finance literature that applies signaling theory to the novel context of ICOs (e.g., Baum and Silverman, 2004; Vismara, 2016). By exploring the roles of different signals of a venture's technological capabilities, the study shows that signaling theory can explain various ICO dynamics. The application of signaling theory to this novel context highlights similarities with more traditional funding settings, while also providing a sound conceptual framework for understanding several particularities of ICOs.

Implications for investors and ventures

ICOs are often described as high-risk investments (e.g., SEC, 2017). For investors, the study's findings indicate that high investment risk can be reduced by a careful evaluation of several characteristics, such as the venture's source code and the technical information provided in a white paper. This also implies that it may be worthwhile for investors to familiarize themselves with DLT in order to be able to more accurately understand the technical information the venture provides. This study further indicates that traditional indicators of venture quality may not be as useful in the ICO context as they are in other domains of entrepreneurial finance. This applies to patents, which do not seem to be an effective signal in the ICO context, as well as human capital variables, which are noisy and not as readily available. Instead, the results indicate that investors seem to consider a different set of indicators that are highly specific to the ICO context, such as the usage of the Ethereum-standard or token supply. In contrast to the technical signals, these determinants may not have any direct association with a venture's underlying capabilities, but seem to influence investors' decision-making. Identifying these determinants and their influence on the funds raised enables investors to more accurately evaluate ICOs in spite of the considerable uncertainty that surrounds them.

The results suggest that ventures with high technological capabilities should make sure to communicate these capabilities because investors assess them to infer the venture's quality and invest accordingly. For example, ventures may find it more useful to reveal their source code or to publish their technological knowledge in a white paper than not doing so. However, ventures face a tradeoff when revealing potentially proprietary information publicly. While signaling higher technological capabilities enables ventures to attract investors, it also allows competitors to imitate their technology more easily. While the results suggest that revealing technological information of high quality is conducive for raising higher amounts of funding, it is unclear whether negative effects (e.g., imitation) might counteract this positive effect in the long run. Ventures should carefully consider this tradeoff when revealing information during their ICO campaign. Further implications for ventures can be derived from the control variables, which suggest multiple factors contribute to raising larger amounts of funding. For example, the results suggest that ventures should utilize the Ethereum-standard and release a greater amount of tokens to increase the amount raised.

Implications for policymakers

The results provide initial insights for policymakers interested in regulating ICOs. While policy development is still in its early stages (e.g., Zetzsche et al., 2017), the results indicate how regulations could be developed further as ICOs gain more widespread adoption. For example, fraudulent ICOs (also referred to as “exit scams”), in which the venture team disappears after raising funds, are a problem that policymakers might want to address (Kean, 2018; Zuckerman, 2018). To counteract such exit scams, policymakers could enforce the publication of the indicators identified in this study that refer to higher venture quality (e.g., require ventures to reveal information about their underlying technology). For ventures with the sole intention to scam investors, it will be impossible or very costly to produce some key technological developments.

Another takeaway is that policymakers interested in spurring DLT ventures and ICOs should not attempt to do so by stimulating patenting. Traditionally, patent-inducing policies, especially aimed at new ventures, are popular among policymakers who wish to encourage innovation (e.g., European Commission, 2018). However, the results show that patents are not an effective signal in the ICO context. Instead, policy initiatives could focus on rewarding or incentivizing ventures according to other relevant technological indicators. For example, indicators could be constructed to reflect the quality of a venture’s white paper or source code.

4.7.2 Limitations and avenues for future research

Limitations

Several issues about data accessibility and quality limit the generalizability of the results. Most of the data were collected manually from a wide array of sources. Many of these sources are manually curated, and so their data are not collected in a standardized way and vary over time. To counteract a potential bias, I cross-referenced every data point between various sources, such as ventures’ websites, white papers, and different ICO-tracking sites. Relatedly, even though CoinSchedule is an established ICO-tracking site, I cannot rule out the possible presence of some selection bias regarding which ICOs are listed. Also, I cannot conclusively state that the coding is affected by some kind of subjectivity.

I was unable to collect data for several variables that might influence the amount raised in ICOs. These include, for example, the amount raised in pre-sales or more detailed data on the venture team. Further, the information included in this study was collected between February and August 2018 (mainly in April 2018). Thus, it cannot be ruled out that some of the information displayed on a venture’s website or on other sites has potentially been altered since the ICO occurred. All information that contains a timestamp, however, was only included until the start of the ICO.

Additionally, even though I argue that a technical white paper is indicative of higher technological capabilities, there is no way to ascertain that this is actually the case for every white paper. For example, ventures may plagiarize others’ work. Also, ventures with low technological capabilities could try to hide behind technical language and descriptions without actually being able to implement these technological advances (Jafery, 2018).

Finally, it is currently unclear whether ICOs will become a major vehicle through which ventures acquire early-stage financing, or whether this trend will cool down quickly. For example, future regulations to limit ICOs, which are not yet developed, could severely impact the field. Despite the present uncertainties, ICOs may very well establish themselves as a crucial mechanism of entrepreneurial finance

Avenues for future research

Future research could explore additional determinants of the amount raised, such as human and social capital (e.g., Ahlers et al., 2015; Allison et al., 2017). While I include variables relating to both concepts, previous research describes a variety of variables that capture them in a much more nuanced way. Specifically, future research could try to operationalize human capital in ICOs by drawing on founder biographies, education, or professional experience. It could also be that ventures employ alternative ways to signal human capital in ICOs. Future studies will be able to draw on larger sample sizes to investigate such variables. Similarly, future studies could try to assess ventures' social capital in ICOs by drawing on network ties between different ventures or focus on the role of advisors in ICOs.

Given the particularities of the ICO context (e.g., faked profiles, anonymity), it is unclear whether human capital plays an equally important role in ICOs as it does in more traditional settings. The results of this study suggest that the importance of human capital may be less pronounced in ICOs, with ventures relying instead on technological characteristics. Future research might find it very interesting to directly compare the importance of different determinants and decision criteria across funding settings. For example, a conjoint analysis could investigate whether human capital is less important to investors in ICOs compared to crowdfunding or venture capital settings, or compared to other ICO characteristics.

Several control variables relate to the amount of funding raised. While a detailed description of the underlying mechanisms is beyond the scope of this study, several interesting avenues for future research emerge. For example, the development of standards may play an important role in the evolution of ICOs. This study suggests that investor's currently value Ethereum-tokens; it would be very interesting to gain a deeper understanding of why this is the case and how this preference develops in the future. Future studies could approach related questions in a more qualitative way. Further, while the variables included in this study suggest that no big differences exist between sectors, a more fine-grained approach may be necessary to uncover potential distinctions. For example, interaction effects between token types and sectors could exist, as security tokens might be more attractive in the finance sector. Even though the results of this study do not reveal any differences between security tokens and utility tokens with regard to the amount raised, investors might opt for a different approach when investing in security tokens in the future.

Additionally, little is known about ICO investors, making it difficult to characterize them convincingly. However, it is crucial to better understand investors in ICOs in order to more comprehensively understand the dynamics of ICOs. Research in crowdfunding often assumes that the average crowdfunding investor makes small contributions and is a less experienced investor (Ahlers et al., 2015; Schaef et al., 2018). It is unclear whether these assumptions can be extended to the ICO context. Future research might thus draw on surveys or qualitative methods and investigate investor characteristics and investment motives in ICOs.

Another crucial avenue for future research is a more careful investigation of the relationship between ICO performance and post-ICO performance. While most ventures intend to develop a product, these ventures often do not have a working product at the time of the ICO. Often, ventures are in such early stages that developments will occur well after the ICO concludes, if at all (e.g., Kaal and Dell'Erba, 2018; Russo and Kharif, 2017). Because of their novelty, few ICOs have a working product as of 2018, making it difficult to assess the post-ICO performance with the limited data available. Future research with access to a broader set of performance data could access how the funding predictors and the funding raised in ICOs relate to future performance. For example, it would be interesting to investigate whether a venture's technological capabilities influence the duration until a venture releases its first product. Also, future research could assess whether ICOs that receive high amounts of funding go on to outperform those that received less, or analyze which determinants may predict future failure. Currently, the valuation of tokens in the secondary market is used as an indicator of (short-term) post-ICO performance. A recent study by Benedetti and Kostovestky (2018) indicates that investors, in general, are able to realize high short-term returns in ICOs. The authors also describe that the amount raised is among the primary determinants of whether an ICO is successful and find a positive association between the amount raised and post-ICO performance. A more careful investigation of how the funding raised in ICOs influences token performance in the secondary market thus presents a final avenue for future research.

Chapter 5

Motives and profiles of ICO investors

The research on initial coin offerings (ICOs) is nascent and assesses ICOs from the perspectives of ventures and regulators. Little is known about the equally important group of investors who provide their capital to ventures in ICOs. Using a primary dataset of 517 ICO investors, we identify and categorize the motivations to invest in ICOs using factor analysis. We find that investors are driven by ideology, technology, and financial motives. Regarding the relative importance of the motives, we find that technological motives are the most important motives to ICO investors, followed by financial and ideological motives. To further profile investors, we conduct a regression analysis to distinguish investors across different motives. For example, we show significant differences across motives with regard to investors' risk perception, sources of information, and the demand for strict regulation. The implications of this study for both theory and practice are considerable.

This chapter is based on

Fisch, C., Masiak, M., Vismara, S., Block, J., 2019. Motives and profiles of ICO investors. *Journal of Business Research*, forthcoming.

5.1 Introduction

An initial coin offering (ICO) represents a novel mechanism of entrepreneurial finance that has substantially gained popularity since 2017. In an ICO (also referred to as a “token offering”), entrepreneurial ventures raise capital by selling tokens to a crowd of investors (Fisch, 2019 [Chapter 4]). Tokens are cryptographically protected digital assets implemented on a blockchain (Li and Mann, 2019).[11] Thus, blockchain technology is at the core of the business models of these ventures. Blockchain technology is a novel and fast-evolving approach to recording and transmitting data across a network in an immutable manner using cryptographic and algorithmic methods (see Natarajan et al., 2017). Blockchain technology is referred to as a revolutionary and disruptive technological innovation with vast potential (e.g., Elnaj, 2018; Swan, 2015). The funding of such highly innovative startups is among the premier topics in entrepreneurial finance (Block et al., 2018a).

ICOs resemble crowdfunding in their approach since they raise funding from a crowd of investors via an open call on the internet. However, one distinguishing characteristic is the concept of selling tokens, which can provide value to investors via a utility or security function. For example, utility tokens can be used to redeem a product or service in the future or can be used as a medium of exchange among users on the venture’s platform. In contrast, security tokens function as investment vehicles and entitle their holders to shares of ownership, dividends, and other financial benefits (e.g., Fisch, 2019; Li and Mann, 2019). During an ICO, investors can buy these tokens directly from the venture that issues them at a predefined price. Therefore, ICO investors provide the venture with early-stage financing that is available to the venture both directly and immediately. In addition, tokens can be traded on a secondary market after the conclusion of the ICO, irrespective of their primary utility or security function (e.g., Adkisson, 2018).

ICOs are controversial. Since they are loosely regulated, they enable startups to raise large amounts of capital while avoiding the costs of compliance and intermediaries. Conversely, the absence of regulation leads to increased investment risk due to misconduct (Cumming et al., 2015), for example, because tokens often have no current counter value and do not lead to any legal entitlement (e.g., Fisch, 2019; Huang et al., 2019, SEC, 2017). This investment risk is particularly high for non-professional investors who do not have the expertise, the resources, and the incentives to perform careful due diligence before investing. As a result, the US Securities and Exchange Commission (SEC) has designed a dedicated website to educate and warn individual investors about possible frauds in ICOs.[12]

[11] Technically, a blockchain is a specific type of distributed ledger technology (DLT), which is the base technology on which blockchains are built. As of 2019, most ICOs are blockchain-based, and blockchain is the most important DLT (Fisch, 2019). In line with most of the prior research, we therefore refer to the term “blockchain” instead of “DLT” throughout this manuscript. However, all of our arguments also apply to ICOs not based on a blockchain.

[12] See https://www.investor.gov/howeycoins (as of July 1st, 2019).

While ICOs are frequently discussed among practitioners, the research on ICOs is nascent. The existing empirical studies mainly investigate the determinants of ICO success (e.g., Ante et al., 2018; Fisch, 2019; Masiak et al., 2019; Momtaz, 2019a) and post-ICO performance (Benedetti and Kostovestky, 2018; Lyandres et al., 2018; Momtaz, 2018). Other studies assess and evaluate ICOs from regulatory, societal, and geographical perspectives (Cohney et al., 2018; Huang et al., 2019).

In contrast, the empirical research on investors, another crucial party involved in ICOs, is non-existent. Thus far, studies have mostly relied on anecdotal evidence regarding the characteristics and motives of investors. For instance, a prominent assumption is that ICO investors primarily seek high returns on investment (e.g., Adkisson, 2018; Cohney et al., 2018; Madeira, 2018). While this assumption appears reasonable, it is unclear whether other motives may play an equally important role. Specifically, research in the related domain of crowdfunding shows that investors are often motivated by a diverse set of extrinsic and intrinsic motives, even though extrinsic motives are often found to be most important (e.g., Allison et al., 2015; Pierrakis, 2019). Relatedly, Vismara (2019) shows that sophisticated crowdfunding investors follow a market logic similar to that of institutional investors, while small investors also consider a community logic (Fisher et al., 2017). This finding suggests that different motivations to invest coincide with different investor characteristics, calling for the profiling of investors according to their investment motives.

Extending this research to the context of ICOs, our goal is to explore and profile ICO investors according to their motives. We assess three interconnected and salient research questions. What are ICO investors' motives to invest in ICOs? What is their relative importance? How can ICO investors be profiled based on their motives?

To answer these questions, we surveyed 517 ICO investors and conducted an exploratory factor analysis to identify the underlying investment motives. Building on self-determination theory (Deci and Ryan, 1985), we find that investors are driven by ideological, technological, and financial motives. Regarding their relative importance, we find that technological motives are more important to ICO investors than financial motives and ideological motives. We then use regression analysis to distinguish and profile the investors according to their motives, revealing significant differences among them. For example, a risk-prone attitude is positively correlated with technological motives, while a professional background in technology is negatively correlated with financial motives. Additionally, earlier ICO investments positively correlate with ideological motives, and the reading of a white paper carefully positively correlates with both ideological and technological motives.

From a theoretical perspective, our findings primarily contribute to the nascent research on ICOs (e.g., Fisch, 2019; Huang et al., 2019; Masiak et al., 2019; Momtaz, 2019a). While this research has assessed ICOs from venture and regulatory perspectives, we assess ICOs from the investor perspective. In addition to identifying a very peculiar set of investment motives and ordering them according to their relative importance, our descriptive statistics and regression analyses enable the profiling of ICO investors for the first time. A better understanding of ICO investors is crucial to understanding and interpreting the increase in ICOs and the associated economic effects.

Additionally, our findings more generally contribute to the research in entrepreneurial finance. Individual investors' motivations have been analyzed with regard to other means of entrepreneurial finance, such as crowdfunding (e.g., Gerber and Hui, 2013; Allison et al., 2015). We extend this research to the context of ICOs by showing that ICO investors are similarly motivated by intrinsic and extrinsic motives. Furthermore, our results indicate that, for ICO investors, intrinsic motives can be more important than extrinsic motives, which could be explained by the fact that ICOs are so far not very popular among professional investors. We highlight the importance of ideological motives in the context of ICOs, which have been parenthetically mentioned in crowdfunding research (Cummings et al., 2019). Furthermore, our profiling provides nuanced insights into how investors' motives relate to different investor characteristics, a topic that has received little attention in prior research.

The practical implications of our study are multifold. Previous studies on equity crowdfunding have shown that the group of investors is highly heterogeneous (Gerber and Hui, 2013; Ryu and Kim, 2016; Vismara, 2019). Similarly, our findings inform ICO-conducting ventures about considerable heterogeneity among investors. Ventures trying to appeal to a broad set of investors should thus make sure to cater to this more nuanced set of motives when trying to attract funding. To policymakers interested in regulating ICOs, our findings can serve as the cornerstone for a more fine-grained approach to developing policies that take into account the differing sets of investment motives. The balance between the need for investor protection and the cost of capital formation is of paramount importance in this context since policymaking is still in its early stages (Huang et al., 2019), and an overly broad regulation might severely undermine the innovative potential of ICOs. As proposed by Hornuf and Schwienbacher (2017), the definition of regulation for new forms of early-stage finance depends on the availability of traditional alternatives. While traditional private equity deals, such as venture capital and business angel financing, are limited to a small group of sophisticated investors, equity crowdfunding and ICOs allow issuers to broadly solicit and advertise their securities to a new pool of small investors. The understanding of their behavior is central to the functioning of entrepreneurial financial markets because such investors are likely to differ from traditional early-stage investors. Additionally, a better understanding of investors is of major importance for policymakers in dealing with financial inclusion and the possibilities of disintermediated entrepreneurial finance. In the eyes of policymakers, financial innovations are intertwined with increased financial inclusion (Cumming et al., 2019b). By profiling different types of investors in ICOs, our paper highlights a different predisposition toward regulation.

5.2 Theoretical framework

5.2.1 Self-determination theory and investor motivations

Self-determination theory (SDT) (Deci and Ryan, 1985) is a theoretical framework that explains human motivation. SDT assesses whether an individual's behavior is self-determined and shows that individuals vary in their type of motivation, which concerns the underlying attitudes and goals that lead to a certain behavior. The most basic distinction is between intrinsic motivation (i.e., doing something because it is inherently interesting or enjoyable) and extrinsic motivation (i.e., doing something because it leads to a separable outcome) (Ryan and Deci, 2000). SDT has been applied to explore the motivations behind a diverse set of behavioral outcomes, such as educational, sports, and organizational behavior (for an overview, see Gagné and Deci, 2005). Additionally, SDT has recently been extended to the domain of entrepreneurial finance to explore individual motives[13] to engage in crowdfunding.

A first set of crowdfunding studies builds on SDT and shows that both extrinsic and intrinsic motivations shape an individual's decision to invest. For example, Gerber and Hui (2013) conduct semistructured interviews with crowdfunding investors and show that investors pursue both extrinsic motives (i.e., collecting rewards) and intrinsic motives (i.e., helping others, being part of a community, or supporting a cause). Allison et al. (2015) confirm these results using a sample of microloans. While the authors show that investors in crowdfunded prosocial microfinance are both intrinsically and extrinsically motivated, they also show that this underlying motivation can be altered through intrinsic and extrinsic cues. Similarly, Bretschneider and Leimeister (2017) survey 309 investors and show that crowdfunding investors are both intrinsically and extrinsically motivated. While these motivations are mainly egocentric, some investors also report prosocial motivations, which is in line with the findings of Allison et al. (2015). Finally, Ryu and Kim (2016) perform a cluster analysis of crowdfunding investors and show that groups of mainly extrinsically motivated and mainly intrinsically motivated investors exist, as well as groups that are mixtures of both. A second, less extensive set of crowdfunding studies explores the relative importance of intrinsic and extrinsic motivations for investments. While the findings are not entirely straightforward, extrinsic motives seem to be generally more important than intrinsic motives. Based on a survey of 630 investors, Pierrakis (2019) shows that individual investors are mainly extrinsically motivated, as the expectation of making a financial return is rated as substantially more important than intrinsic motives. Additionally, Vismara (2016) finds that the presence of rewards does not impact the chance of success of equity crowdfunding offerings. Considering that, in equity crowdfunding, rewards (e.g., a shirt or a plaque of appreciation) often have little objective value, the decision to invest is predominantly motivated by the opportunity

[13] SDT does not emphasize a clear distinction between the terms "motivations" and "motives". In line with prior research in entrepreneurial finance, we therefore use the terms synonymously.

to take an equity position in the issuing firm. Therefore, Pierrakis (2019) and Vismara (2016) conclude that financial returns are the main driver of investments in investment crowdfunding. In contrast, a working paper by Daskalakis and Yue (2017) finds that nonfinancial motives, such as interest and excitement, are more important drivers of investments in equity crowdfunding.

5.2.2 Individual motives to invest in ICOs

Building on these crowdfunding studies, we outline the peculiarities of the ICO context, which provide initial insights into the potential motives of ICO investors. Similar to the context of crowdfunding, we argue that ICO investors are likely driven by both intrinsic and extrinsic motives.

Intrinsic motives of ICO investors

Gerber and Hui (2013) outline that investors in crowdfunding can be motivated by supporting a cause that is analogous to their personal beliefs, which reflects ideological reasons. Similarly, we argue that ideological reasons are an important intrinsic motive of ICO investors.

Bitcoin's white paper (Nakamoto, 2008) is a cornerstone of blockchain technology and outlines two influential factors that have shaped the evolution of the blockchain sector from a technological and ideological point of view: (1) anonymity and (2) decentralization (Iansiti and Lakhani, 2017). First, Bitcoin's white paper proposes a method to enable anonymous transactions. This desire for anonymity, which is at least partially ideological, characterizes most developments based on blockchain technology, including most ICOs (e.g., Kastelein, 2017). The pronounced interest in anonymity applies to ICO investors and venture teams. For example, information on venture teams is not as readily available as in other domains of entrepreneurial finance, as some teams choose to remain anonymous or to not provide too much personal information (Fisch, 2019). This desire for anonymity also affects ICO investors, as investments in ICOs are usually pseudonymous (i.e., it is possible to track the source of a transaction, but the source's identity remains unknown) (Kastelein, 2017). Second, Bitcoin's white paper focuses on enabling a higher degree of decentralization. Mostly, this refers to enabling transactions without intermediaries, thus reducing complexity in many processes or industries (Chambers, 2018). Therefore, blockchain technology has the potential to democratize a number of fields. Entrepreneurial finance, where the demand for democratization and disintermediation is high (Cumming et al., 2019b), is one such field.

Similarly, crowdfunding research describes the personal interest of investors in the venture's product or business model as another intrinsic investment motive (e.g., Ryu and Kim, 2016; Pierrakis, 2019). Similarly, we assume that an interest in the product or business model behind the respective ICO and blockchain technology is another investment motive of ICO investors. The future success of an ICO venture largely depends on its ability to build on and use this technology (Cohney et al., 2018; Fisch, 2019). The high importance of technology is also reflected in the information provided by ICO ventures. For example, the revealing of source code and providing of white papers with a high degree of technological information are crucial (e.g., Cohney et al., 2018; Fisch, 2019). The highly technical environment implies that investors will benefit from technological knowledge to understand the technical background and application proposed by each project. This argument is supported by recent empirical evidence, which shows that the indicators of technological capabilities are important signals in the ICO context and help ventures to attract more funding (Fisch, 2019). ICO investors, therefore, seem to value the technology of ICO ventures.

Extrinsic motives of ICO investors

Studies on investors' motives in crowdfunding highlight the crucial importance of extrinsic motives (e.g., Allison et al., 2015; Gerber and Hui, 2013). Similar to crowdfunding, ICOs serve an investment function, as they constitute a mechanism to invest in innovative ventures by buying tokens. To some extent, the capital provision function is the core idea behind ICOs. Hence, ICOs represent future-oriented investment opportunities. As with other investment opportunities, achieving high investment returns is thus a major motivation of ICO investors (e.g., Adkisson, 2018; Benedetti and Kostovestky, 2018; Cohney et al., 2018).

The tokens sold in ICOs are flexible and can function as investment vehicles by referring to tradeable assets in a form similar to that of securities. To this extent, ICOs resemble traditional initial public offerings in that they provide entrepreneurs with the opportunity to raise fresh capital in the primary market. Here, tokens resemble other kinds of traditional securities and entitle the holder to dividends or other financial benefits (e.g., Fisch, 2019; Sameeh, 2018). Ultimately, this leads to higher implicit returns on investment. Nevertheless, while traditional equity and debt securities come with specific and enforceable legal rights, tokens do not.

ICOs are also of interest for secondary market reasons. A particularity of tokens is that they can be traded after an ICO is concluded (e.g., Benedetti and Kostovestky, 2018; Lyandres et al., 2018). Indeed, as of 2019, a multitude of exchanges exist that enable investors to trade tokens against traditional currencies or other tokens. Hence, an increased post-ICO valuation of the token enables investors to sell the token to receive a return on their investment. Since the volatility of the price of tokens can be high, they are attractive for short-term investors because of hedging and arbitrage opportunities (e.g., flipping). This volatility may, therefore, attract investors looking for investment opportunities with a high risk-return profile. This function of tokens is frequently highlighted as a main feature of ICOs (e.g., Adkisson, 2018; Madeira, 2018), whereby confident investors are tempted by the prospect of identifying the "next Bitcoin" (Fisch, 2019; Mourdoukoutas, 2018). Previous studies have indeed shown that investors often overweight low probability events and exhibit a preference for investment opportunities with positive skewness, emphasizing the potential role of gambling in investment decisions (Kumar, 2009). An extrinsic motivation to invest in ICOs might, therefore, be in line with Markowitz (1952) conjectures that some investors might prefer to "take large chances of a small loss for a small chance of a large gain".

5.3 Empirical approach

5.3.1 Survey and dataset

We surveyed ICO investors and collected information on (1) investment motives when investing in ICOs, (2) sociodemographic information, and (3) ICO investment behavior.

An established database of ICO investors does not exist. Consequently, it is very difficult to identify ICO investors. We thus relied on self-selection sampling and approached potential participants via an open online call. Specifically, we posted a link to our survey on a multitude of online platforms that frequently discuss ICOs and where ICO investors are likely present, such as Reddit (social news aggregator), Twitter, Facebook, LinkedIn, Telegram (messaging service), and Bitcointalk (forum dedicated to cryptocurrencies). The survey was initially posted in June 2018. Participants were able to participate until August 2018. As an incentive, we offered a detailed report of the results and a chance to win 0.5 Ether[14] as a reward for participation.

Over a period of 7 weeks, the survey was viewed 4,119 times. A total of 719 individuals started the survey, and 541 individuals completed the survey. Since we were only interested in surveying ICO investors (i.e., individuals who had previously invested in at least one ICO), we excluded 19 respondents who stated that they had never invested in an ICO. Another 5 responses were excluded because of missing values. Hence, the final sample comprised 517 ICO investors.

The survey was conducted anonymously to fully comply with the latest data security legislation (EU-GDPR/18 General Data Protection Regulation). Additionally, previous research shows that anonymous surveys are particularly suitable when collecting sensitive information (e.g., financial information). This is because the responses are often more truthful, which is important for our research (e.g., Block et al., 2019b [Chapter 2]; Graham and Harvey, 2001). However, we were able to track the origin of each response if the respondent directly clicked on the survey link on a website. Specifically, 118 (22.8%) of the responses originated from Reddit, 143 (27.7%) from LinkedIn, and 73 (14.1%) from other sources such as Twitter and Facebook. We were unable to track the origin of 183 responses (35.4%).

[14] Ether is a widespread cryptocurrency, which is based on the Ethereum ecosystem. In August 2018, the value of 0.5 Ether was approximately 280 $.

Since we conducted a survey, we assessed the possibility of late-response bias. Late respondents resemble nonrespondents, and the results might be biased if late respondents are significantly different from early respondents (e.g., Armstrong and Overton, 1977; Graham and Harvey, 2001; Block et al., 2019b). We divided our sample of 517 respondents into early respondents (first 129 respondents, 25% of the sample) and late respondents (last 129 respondents, 25% of the sample). No major group differences existed (Appendix, Table 5.A1).

5.3.2 Variables and descriptive statistics

Table 5.1 outlines the definitions of the variables as well as the descriptive statistics. The selected variables are graphically illustrated in Figure 4.1.

Measuring motives to invest in ICOs

The first group of variables captures investors' motives to invest in ICOs. We use a broad set of nine items that comprise both intrinsic and extrinsic motives. The items were inspired by previous research in the domain of crowdfunding (e.g., Ryu and Kim, 2016; Pierrakis, 2019). However, since an established and validated set of ICO investor motivations does not exist, we adapted existing extrinsic and intrinsic motives to the specific context of ICOs. We also talked to several ICO investors using informal interviews when developing the items.

To measure the importance of the motives, we asked respondents to rank each item on a 5-point Likert scale, ranging from 1 ("not important at all") to 5 ("very important"). Our first set of items refers to ideological reasons and highlights the personal and/or societal utility that is attainable when investing in ICOs ("use tokens in their intended utility function (e.g., governance, transactions)", "social motives (e.g., sustainability, philanthropy)", "disrupting established structures and/or industries (e.g., decentralization, anonymity)" and the ICO's technology and business ("personal enthusiasm for the technology of the ICO venture" and "personal enthusiasm for the business model or business idea of the ICO venture"). Furthermore, we include a second set of items to capture the extrinsic motives related to ICOs as a currency or investment vehicle ("future sale of the token at a higher price (shortly after the ICO)", "future sale of the token at a higher price (at a later point in time)", "gaining an equity stake in the ICO venture", and "financial gains (e.g., dividends)").

We describe the respective items and their importance in more detail in Section 4.2.

Table 5.1: Description of variables, coding, and descriptive statistics

Variable	Coding	M	SD	Min	Max
Reasons to invest	**In general, how important are the following motives in your decision to invest in ICOs? (1 = not important; 5 = very important)**				
Utility	Use tokens in their intended utility function (e.g., governance, transactions)	3.38	1.23	1	5
Social	Social motives (e.g., sustainability, philanthropy)	2.90	1.26	1	5
Disruption	Disrupting established structures and/or industries (e.g., decentralization, anonymity)	3.87	1.15	1	5
Technology	Personal enthusiasm for the technology of the ICO venture	4.13	0.93	1	5
Business model	Personal enthusiasm for the business model or business idea of the ICO venture	4.23	0.83	1	5
Sale (short-term)	Future sale of the token at a higher price (shortly after the ICO)	3.31	1.33	1	5
Sale (long-term)	Future sale of the token at a higher price (at a later point in time)	4.24	0.93	1	5
Equity stake	Gaining an equity stake in the ICO venture	3.07	1.18	1	5
Financial gains	Financial gains (e.g., dividends)	3.69	1.15	1	5
Sociodemographics					
Age	Respondent age (in years)	32.86	8.66	16	65
Gender	Dummy variable that captures whether the respondent is male (= 1) or not (= 0)	0.95	-	0	1
Residence: US	Dummy variable that captures whether the respondent currently resides in the US (= 1) or not (= 0)	0.15	-	0	1
Residence: EU	Dummy variable that captures whether the respondent currently resides in Europe (= 1) or not (= 0)	0.53	-	0	1
Risk-taking	Q: Are you generally a person who is willing to take risks? (1 = not at all willing to take risks; 10 = very willing to take risks)	7.34	1.67	1	10
Level of education	Respondents' highest educational degree (1 = no schooling completed; 6 = doctorate degree)	4.10	1.09	1	6
Edu: Business	Dummy variable that captures whether the respondent's main field of study was business/economics (= 1) or not (= 0).	0.32	-	0	1
Edu: Computer sciences	Dummy variable that captures whether the respondent's main field of study was computer sciences (= 1) or not (= 0).	0.23	-	0	1
Occ: Self-employed	Dummy variable that captures whether the respondent is currently self-employed (= 1) or not (= 0)	0.36	-	0	1
Occ: Employee	Dummy variable that captures whether the respondent is currently an employee (= 1) or not (= 0)	0.49	-	0	1
Prof: Technology	Dummy variable that captures whether the respondent's professional background is mainly in technology (= 1) or not (= 0)	0.39	-	0	1
Prof: Finance	Dummy variable that captures whether the respondent's professional background is mainly in finance (= 1) or not (= 0)	0.16	-	0	1
Investment knowledge	Q: Please rate your overall investment knowledge (outside the cryptosphere). (1 = no knowledge; 5 = very good)	3.56	0.96	1	5
ICO investment behavior					
First investment	Number of years since the respondent's initial ICO investment	1.09	1.01	0	5
No. of ICO investments	Q: How many ICOs did you invest in so far? (continuous variable from 1 to 20 or more)	6.65	6.57	1	20
Investments (in $)	Q: In total, how much did you invest in ICOs so far? (categorical, 1 = < 250 $; 8 = > 100,000 $)	4.17	2.19	1	8
Afraid of fraud	Q: Are you afraid of fraud when investing in ICOs? (1 = very much; 5 = not at all)	2.60	0.54	1	5
Need for regulation	Q: Level of agreement with the statement: "ICO regulation should be more strict" (1 = strongly disagree; 5 = strongly agree)	3.50	1.18	1	5
Read white paper	Q: Do you usually read the ICO's white paper before investing? (1 = no; 4 = I read the white paper and try to understand every detail)	3.09	0.78	1	4

Notes: N = 517. Reference group for residence dummies = rest of the world. Reference group for education dummies = no education/other education. Reference group for occupation dummies = student/retiree/other. Reference group for professional background dummies = other. [a] N = 497, as a response was not mandatory.

Sociodemographic characteristics

The second group of variables captures sociodemographic characteristics. Respondents were initially asked to indicate their age and gender. The average respondent was 32.9 years old (minimum 16; maximum > 65). The majority of respondents were male (95.4%). With regard to geographical distribution, the largest groups of respondents come from the US (14.7%), Germany (11.6%), and the Netherlands (9.5%). In sum, 52.6% of the respondents were European. The sample comprises respondents from 66 countries, indicating a considerable geographic spread.

The average level of education is rather high, as more than 81.7% of respondents hold a bachelor's degree or higher. Regarding respondents' main fields of study, 32.3% indicated that they have an educational background primarily in business or economics, while 22.8% indicated that they have a background in computer sciences. The remaining respondents are scattered across different disciplines or did not study at all. A share of 48.9% of the respondents is currently working as an employee, while 36.4% of respondents are self-employed. The remaining group comprises students, retirees, and others. Moreover, 38.9% of the respondents have a professional background in the technology sector, while 15.7% have a background in finance. To assess the risk-taking attitude of investors, we asked respondents to rate how generally willing they are to take risks on a scale from 1 to 10. This measurement is taken from the German Socio-Economic Panel (DIW Berlin, 2016). With a value of 7.34, the average risk tolerance in our sample seems to be rather high.

Finally, we asked respondents to rate their investment knowledge outside of ICOs. The average value is 3.56, indicating a certain degree of experience. To delve into this topic more deeply, we asked respondents for their specific experience with different investment vehicles (not included in Table 5.1). A total of 41.6% of the respondents indicated that they had previously invested in investment funds, which was the most common investment vehicle mentioned. Investment funds were closely followed by stocks, in which 41.5% of the respondents had already invested. The overlap with crowdfunding is not as large as we expected it to be: 23.0% of the respondents indicated that they had previously engaged in crowdfunding. Finally, 19.1% of respondents indicated that they had no prior investment experience. Crowdfunding research often assumes that investors are novices (e.g., Schaef et al., 2018). Our findings suggest that this assumption may not be universally extendable to the context of ICOs.

ICO investment behavior

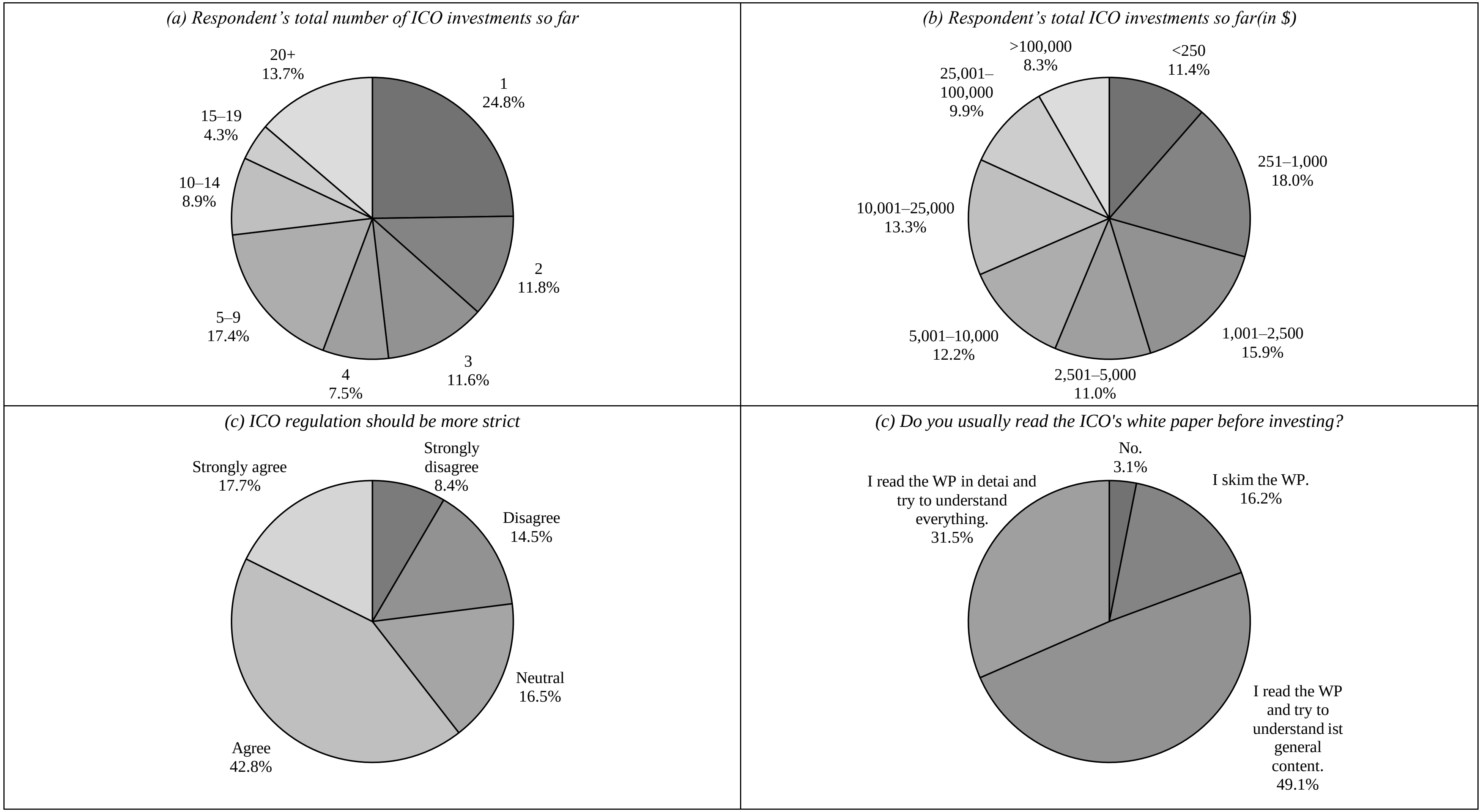
The final set of variables captures information on respondents' ICO investment behavior. Initially, we asked respondents about the date of their first investments. The first ICO ever took place in 2013, and 13 respondents indicated that they had indeed initially invested in 2013. We constructed a variable that captures the time elapsed since respondents' first investment as of 2018. The average value is 1.1, indicating that most respondents had first invested in an ICO in 2017.

We then asked respondents about the number of their ICO investments so far and constructed a continuous variable, with values ranging from 1 to 20. The average number of investments is 6.6. While 128 respondents had only invested in one ICO, 71 respondents had invested in 20 or more ICOs. This distribution is graphically illustrated in panel (a) of Figure 5.1. We asked respondents about the total amount of money they had invested in ICOs. We used a categorical variable, ranging from 1 (invested less than 250 $) to 8 (invested more than 100,000 $). The results reveal an equal distribution across the eight categories: 11.4% of the respondents invested less than 250 $, 12.2% invested between 5,001 and 10,000 $, and 8.3% invested more than 100,000 $. This distribution, which is illustrated in panel (b) of Figure 5.1, indicates that it is difficult to characterize the average investor in ICOs with regard to the amount invested.

The amount of reliable information on ICOs is often low, a considerable potential for fraud exists, and policy development is in its early stage (Huang et al., 2019). We, therefore, asked respondents about their perception of fraud via the following question: "are you afraid of fraud when investing in ICOs?" (1 = very much; 5 = not at all). With a mean value of 2.60, respondents seem to be slightly afraid of fraud. A total of 76 respondents (14.7%) are very afraid, and 205 (39.7%) are afraid of fraud. In contrast, 26 respondents (5.0%) stated that they are not afraid of fraud at all. Relatedly, we asked respondents to indicate their level of agreement with the following statement: "ICO regulation should be more strict" (1 = strongly disagree; 5 = strongly agree). Similarly, investors are slightly in favor of more regulation (mean = 3.50), as illustrated in panel (c) of Figure 5.1.

A white paper is a document in which a venture provides information to the public and constitutes an important component of a venture's ICO campaign (e.g., Cohney et al., 2018; Fisch, 2019). However, a white paper can only serve its function if it is actually read. Anecdotal evidence suggests that investors often do not read white papers (May, 2017). Therefore, we asked respondents whether or not they usually read the ICO's white paper before investing. Possible answers were "no" (coded as 1), "I skim the white paper" (coded as 2), "I read the white paper and try to understand its general content" (coded as 3), and "I read the white paper in detail and try to understand everything" (coded as 4). The mean value of 3.1 indicates that white papers are generally read by our respondents. Specifically, only 16 (3.1%) respondents stated that they generally do not read white papers, while 163 (31.5%) indicated that they "read the white paper in detail and try to understand everything". This distribution is further illustrated in panel (d) of Figure 5.1.

Figure 5.1: Illustration of selected responses (N = 517 ICO investors).



5.4 Results

5.4.1 Factor analysis to identify groups of investment motives

We conduct an exploratory factor analysis to categorize and aggregate investment motives. Factor analysis provides internally consistent factors and focuses on the constructs underlying the individual items.

Specifically, we conduct a principal component factor analysis with varimax rotation. The results indicate a three-factor solution according to the latent root criterion (i.e., three factors have eigenvalues greater than 1) (e.g., Block et al., 2015; Thomä and Bizer, 2013). To assign items to specific factors, we employ a threshold of 0.50 for the varimax-rotated factor loadings. Table 5.2 depicts the rotated factor loadings and extracted variances. Eight of the 9 items load unambiguously onto one of the three factors and are thus assigned to only one factor. Item 6 does not meet the minimum threshold for either factor and shows a considerable cross-loading. We thus omitted that item from our factor analysis (Osborne et al., 2008).[15]

Table 5.2: Factor analysis of motives for investing in ICOs

Variable	**Factor 1**	**Factor 2**	**Factor 3**
Interpretation	*Ideology motives*	*Technology motives*	*Financial motives*
1. Use tokens in their intended utility function	**0.64**	0.21	0.28
2. Social motives	**0.57**	0.32	0.24
3. Disrupting established structures/industries	**0.54**	0.28	0.17
4. Personal enthusiasm for the technology	0.21	**0.80**	-0.04
5. Personal enthusiasm for the business model/idea	-0.01	**0.85**	0.08
6. Future sale of the token shortly after the ICO	-0.48	-0.10	0.45
7. Future sale of the token at a later point in time	**-0.56**	0.28	-0.24
8. Gaining an equity stake in the ICO venture	0.24	0.03	**0.74**
9. Financial gains	-0.02	0.05	**0.78**
Variance explained	26.4%	16.2%	12.7%
Cronbach's α	0.54	0.67	0.60

Notes: N = 517 ICO investors. Principal component analysis, varimax-rotated factor loadings. Kaiser–Meyer–Olkin measure: 0.662, Bartlett's test of sphericity: 626.08, $p < 0.01$. Factor loadings assigned to the respective factors are highlighted in bold.

The three factors account for 55.3% of the total variance among respondents' answers. A major assumption of factor analysis is that the factor variables are correlated. To test this assumption, we use Bartlett's test of sphericity (626.08, $p < 0.01$), which indicates that the variables used in the factor analysis are correlated and not independent of one another. The Kaiser–Meyer–Olkin measure (KMO = 0.66) also indicates a sufficient fit of the data. Hence, both measures indicate that the dataset is appropriate for factor analysis.

[15] However, the item is considered when estimating the factor scores, which we use as the dependent variable in our regression analyses (Section 5.4.3).

In the following subsections, we describe each factor in detail. We label the factors as follows: (1) ideological motives, (2) technological motives, and (3) financial motives. While ideological and technological motives reflect an intrinsic motivation, financial motives reflect an extrinsic motivation of ICO investors.

Factor 1: Ideological motives

Factor 1 has the largest eigenvalue and explains the most variance (26.4%) of the extracted factors. The factor reflects an intrinsic investment motivation and comprises the items “use tokens for their intended utility function”, “social motives”, “disrupting established structures and/or industries”, and “future sale of the token at a higher price (at a later point in time)”. We label this factor “ideological motives” because all items can be related to the underlying ideology that characterizes the blockchain sector and the field of ICOs.

Two of the major drivers behind the development of blockchain technology, specifically cryptocurrencies, are the desire to enable anonymous transactions and a higher degree of decentralization (Iansiti and Lakhani, 2017). Both motives are at least partially ideology-driven and were initially outlined in Bitcoin’s white paper (Nakamoto, 2008). Since then, the potential of blockchain technology has been clarified, extended, and widely discussed (e.g., Elnaj, 2018; Swan, 2015). However, blockchain technology is affected by a considerable degree of uncertainty, and it is currently unclear whether blockchain technology will live up to its potential (Natarajan et al., 2017). High scores in Factor 1 point to investors believing in the (future) potential and ideology of blockchain technology in spite of the present uncertainties. This view is substantiated by the considerable negative factor loading of the extrinsic motive “future sale of the token at a higher price (at a later point in time)”. This finding also indicates that investors intend to hold on to tokens to realize the investments’ future potential instead of selling them shortly. This implies a longer time horizon of investors, as the potential of most blockchain projects and the changes intended cannot be immediately realized. In particular, ICOs might underline blockchain projects at very early stages, and it is often unclear whether and how these projects will eventually succeed. For some tokens, this might affect the possibility of developing a liquid secondary market.

Factor 2: Technological motives

Factor 2, labeled “technological motives”, explains 16.2% of the variance and comprises the items “personal enthusiasm for the technology of the ICO venture” and “personal enthusiasm for the business model/idea”. Both items have high positive factor loadings and show a clear intrinsic motivation of ICO investors.

In the past, new players in entrepreneurial finance have emerged due to technological advances (Block et al., 2018a). Similarly, ICOs only suit ventures that (intend to) use blockchain technology, a creative yet complex and highly technological innovation (Natarajan et al., 2017; Swan, 2017). Hence, technology is at the heart of most ventures that conduct an ICO and the ventures' technology, and the ventures' technological capabilities can serve as a crucial indicator of their future success (Fisch, 2019). Investors with high factor scores rate ICOs' technological background as crucial to their investment decisions. Since technology is at the core of most ICOs, it cannot be disconnected from the business itself.

Factor 3: Financial motives

Factor 3 explains 12.7% of the variance and represents more traditional financial motives. The factor comprises the items "gaining an equity stake in the ICO venture" and "financial gains", such as dividends. This factor reflects an extrinsic motivation to invest in ICOs.

First and foremost, ICOs are a means of new venture finance (Fisch, 2019). It is thus unsurprising that one set of motives refers to ICOs as an investment, for example, to realize portfolio diversification or financial returns. Hence, ICOs function as a securities investment.

While tokens sold in ICOs function as a venture's initial financing, most tokens can be sold in a secondary market after the ICO's conclusion (e.g., Benedetti and Kostovestky, 2018; Lyandres et al., 2018). Interestingly, this factor does not comprise the items pertaining to the sale of tokens in the secondary market but refers to ICOs as a more traditional form of securities investment. Therefore, individuals with high factor scores treat ICOs as a security, which is different from the speculative notion that is often portrayed in the media (e.g., Adkisson, 2018; Madeira, 2018).

5.4.2. The relative importance of investment motives

In addition to identifying groups of motives, we are interested in the relative importance of the motives. Prior research has indicated that investors in crowdfunding often consider extrinsic motives to be more important than intrinsic motives (e.g., Vismara, 2016; Pierrakis, 2019).

Table 5.3 enables initial insights into the importance of investment motives. Investors rate the ability to sell the token at a higher price as the overall most important reason to invest in ICOs (mean = 4.24). A total of 242 respondents (46.8%) rated this item as "very important", while only 11 (2.1%) rated it as "not important at all". The second most important reason to invest in ICOs is a personal enthusiasm for the business model/idea (4.21) and technology (4.11). These results suggest that high investment returns through the sale of tokens are indeed a major motivation of ICO investors. In line with the prior research on crowdfunding, the most important reason to invest in ICOs is extrinsically motivated. However, the results also show that the business model/idea is nearly as important as the future sale of the token, as the difference in importance is not statistically significant. This also indicates that investors seem to be simultaneously driven by multiple motives.

In contrast to the sale of a token at a later point in time, the sale of the token shortly after the ICO is less important to investors (3.30). Investors rate gaining an equity stake in a company (3.05) as even less important. This low importance of gaining an equity stake might distinguish ICOs from more traditional forms of finance, such as IPOs and equity crowdfunding. However, this low importance is not entirely surprising, as pure security tokens (which can entitle the token holder to an equity share) were comparatively rare when the survey was conducted (Fisch, 2019). Respondents rated social motives as least important (2.90). Since two out of the three least important motives reflect extrinsic motivations, it is difficult to make a general assessment of the overall importance of intrinsic and extrinsic motives. This is also reflected in the considerable variance in the responses, as illustrated in Table 5.3.

Table 5.3: Reasons to invest in ICOs and their importance

	Importance						
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**Mean**	**Rank**
Utility	48 9.3%	88 17.0%	98 19.0%	186 36.0%	97 18.8%	3.38	6
Social	90 17.4%	118 22.8%	117 22.6%	139 26.9%	53 10.3%	2.90	9
Disruption	27 5.2%	50 9.8%	69 13.4%	189 36.6%	182 35.2%	3.87	4
Technology	12 2.3%	31 6.0%	31 6.0%	257 49.7%	186 36.0%	4.11	3
Business model	10 1.9%	15 2.9%	31 6.0%	259 50.1%	202 39.1%	4.21	2
Sale (short-term)	47 9.1%	136 26.9%	72 13.9%	139 26.9%	123 23.8%	3.30	7
Sale (long-term)	11 2.1%	25 4.8%	36 7.0%	203 39.3%	242 46.8%	4.24	1
Equity stake	59 11.4%	110 21.3%	150 29.0%	140 27.1%	58 11.2%	3.05	8
Financial gains	28 5.4%	64 12.4%	94 18.2%	194 37.5%	137 26.5%	3.67	5

Notes: N = 517 ICO investors. Importance rated on a 5-point Likert scale (1 = not important at all; 5 = very important).

In addition to assessing the importance of the items used in our survey, we assess the importance of each factor. Table 5.4 reveals that ICO investors consider technological motives to be most important (mean importance = 4.16). Financial motives rank second (mean importance = 3.36), and ideological motives rank third (mean importance = 2.98). This result is surprising, as it differs from those of prior (crowdfunding) research by indicating that intrinsic motives seem to be at least partially more important to ICO investors than extrinsic motives. Our findings highlight that the ICO context might be unique in this regard. This could be explained by the fact that the share of professional investors in ICOs is still low and that the nature of ICOs differs from that of other financing instruments (e.g., crowdfunding). In particular, the characteristics of blockchain technology (e.g., decentralization, peer-to-peer transactions, transparency, irreversibility, and computational logic) play a considerable role in ICOs. In other words, the technology itself is not only the core of the financing vehicle but also inseparable from the process of the actual investment in a venture. If an investor wants to invest in an ICO, the investor must be familiar with, for instance, tokens, digital wallets, trading exchanges, and cryptocurrencies. Hence, technological motives may be more prominent in the context of ICOs.

Finally, Table 5.4 includes the share of ICO investors who consider the respective motive as most important. While, as discussed above, technology factors are on average considered important (4.16), the results displayed in the final column indicate that 37.9% of the respondents rate financial motives as most important. While technological factors are broadly relevant for investors, more than one-third of investors are attracted to ICOs mostly because of the prospects of financial returns. On the other hand, ideological motives rank last. Nevertheless, they are rated as the most important motives to invest in ICOs by 27.9% of the respondents. This means that, while some investors appear insensitive to ideological motives (e.g., social motives are considered "not important at all" by 17.4% of the respondents), others care passionately about them. Overall, these results indicate that ICOs blend different types of investors together.

Table 5.4: Motives to invest in ICOs and their importance

Factor	Mean importance	Rank	Most important factor for
Factor 1: Ideological motives	2.98	3	144 (27.9%)
Factor 2: Technological motives	4.16	1	177 (34.2%)
Factor 3: Financial motives	3.36	2	196 (37.9%)

Notes: N = 517 ICO investors. Importance rated on a 5-point Likert scale (1 = not important at all; 5 = very important). Factor 1 comprises items 4 (reverse coded), 7, 8, and 9; Factor 2 comprises items 1 and 2; Factor 3 comprises 5 and 6 (as described in Table 5.1).

5.4.3 Regression analysis to profile investors according to their investment motives

We build on the results of the factor analysis and conduct a regression analysis to identify the correlates of high scores across different motives. This allows us to further investigate the heterogeneity in investors' motives by enabling identification and comparison of the correlates of different motives.

The three factors identified by the exploratory factor analysis constitute the dependent variables. The factor scores were generated by a regression-based approach, which weights the items by their respective factor loadings. The regression approach maximizes the validity of the predicted scores, as it produces the highest correlations between factor scores and factors (e.g., DiStefano et al., 2009). Importantly, every item is used to predict the factor scores (including item 3), so no information provided by the respondents is omitted when predicting the factor scores and, subsequently, when profiling investors.

The correlations and variance inflation factors are displayed in Table 5.A2 (Appendix). As a result of the factor analysis, the factors are uncorrelated. Additionally, the correlations and variance inflation factors indicate that multicollinearity should not bias our estimates. The results of the OLS regression analysis are displayed in Table 5.5.

Table 5.5: Profiling ICO investors according to investment motives

	Model 1	Model 2	Model 3
Dependent variable	**Ideological motives**	**Technological motives**	**Financial motives**
Variables	**Coeff. (SD)**	**Coeff. (SD)**	**Coeff. (SD)**
Sociodemographics			
Age	-0.009 (0.005)*	0.010 (0.005)*	0.000 (0.005)
Gender	-0.301 (0.207)	-0.202 (0.211)	0.056 (0.208)
Residence: US	0.051 (0.137)	0.162 (0.140)	-0.151 (0.138)
Residence: EU	-0.027 (0.100)	-0.014 (0.101)	-0.340 (0.100)***
Risk taking	-0.063 (0.027)**	0.066 (0.027)**	0.041 (0.027)
Level of education	-0.058 (0.041)	-0.030 (0.041)	-0.032 (0.041)
Education: Business	0.052 (0.108)	-0.037 (0.110)	-0.127 (0.108)
Education: Computer sciences	0.037 (0.124)	0.163 (0.126)	0.015 (0.125)
Occupation: Self-employed	0.057 (0.143)	0.072 (0.146)	0.025 (0.144)
Occupation: Employee	0.121 (0.132)	0.181 (0.135)	-0.117 (0.133)
Professional background: Technology	0.011 (0.137)	-0.164 (0.139)	-0.349 (0.137)**
Professional background: Finance	0.217 (0.108)**	-0.127 (0.109)	-0.244 (0.108)**
Investment knowledge	0.082 (0.050)	0.045 (0.051)	-0.058 (0.050)
ICO investments			
First investment	0.145 (0.044)***	0.007 (0.044)	-0.053 (0.044)
No. of ICO investments	-0.001 (0.008)	-0.002 (0.008)	0.018 (0.008)**
Investments (in $)	-0.013 (0.026)	0.008 (0.026)	-0.057 (0.026)**
Afraid of fraud	0.079 (0.041)*	-0.007 (0.041)	-0.077 (0.041)*
Need for regulation	0.015 (0.039)	0.008 (0.039)	0.097 (0.039)**
Read white paper	0.234 (0.057)***	0.215 (0.058)***	0.018 (0.057)
R^2	0.106	0.073	0.099
R^2 (adj.)	0.072	0.038	0.065

Notes: N = 517 ICO investors. OLS regression with the factor scores obtained from the factor analysis as the dependent variable. * p < 0.10, ** p < 0.05, *** p < 0.01. Reference group for residence dummies = Rest of the world. Reference group for education dummies = no education/other education. Reference group for occupation dummies = student/retiree/other. Reference group for professional background dummies = other.

Factor 1: Ideological motives

The high scores in ideological motives correlate with an earlier first ICO investment. This suggests that ideology is one of the main drivers behind the development of ICOs and indicates that initial investors were particularly attracted by ideological motives. Additionally, the potentials of blockchain technology were more abstract and not as well developed and understood when ICOs were initially introduced. Hence, ideological reasons may have been one of the most important drivers in the early development of ICOs. Interestingly, investors with high scores in ideological motives also correlate with higher risk aversion and fear of fraud. Ideological reasons may overlay these investment risks and bring these individuals to invest in ICOs, even though they would otherwise shy away from the high investment risk associated with them. The high scores in ideological motives also correlate with the fact that ICO investors read white papers more carefully. This is unsurprising, as a white paper is the main document in which ICOs outline the ideological background and intended contributions of their project. Furthermore, investors must rely primarily on white papers to detect possible fraud. Since ideologically motivated investors appear to be relatively risk-averse, they read white papers more carefully.

Factor 2: Technological motives

The high scores in technological motives correlate with high values in risk-taking. This indicates that these individuals are confident in blockchain technology and its potentials. As of 2019, it is still unclear whether blockchain technology will become the major and radical technological innovation that is often postulated, as not all technological problems have been solved (Natarajan et al., 2017). Specifically, ICOs often do not have a working product or prototype and provide very preliminary technological solutions (Shifflett and Jones, 2018). However, investors with a strong technological motivation are not discouraged by this present uncertainty, as reflected in their higher degree of risk tolerance. Additionally, reading white papers very carefully correlates with high scores in technological motives. This underlines the important role of white papers as a primary source of information in ICOs. Specifically, the technological information presented in a white paper seems to be of crucial interest to this group of investors (Fisch, 2019). This finding also contradicts anecdotal evidence that questions the role of white papers and suggests that investors often do not read white papers (May, 2017). However, this result could also be attributed to potential selection bias: less-informed investors that were mainly driven by hype may have been less likely to read white papers and may have already left the market in mid-2018 due to a sharp decline in cryptocurrency valuations.

Factor 3: Financial motives

The high scores in financial motives correlate with a more conservative approach to investing in ICOs. While they correlate with a higher number of overall ICO investments, they also correlate with lower amounts of money invested. Both characteristics indicate a strategy of portfolio diversification via ICO investments. An additional finding is that these investors seem to be more afraid of fraud and of the opinion that the regulation of ICOs should be stricter. This reinforces the argument that stricter regulation is primarily sought by investors with a financial motivation who demand a safe environment for their investments. Moreover, these investors are less often from Europe, indicating that ICOs may be a less prominent investment vehicle in Europe compared to the rest of the world. The results further indicate that financial motives are less appealing to investors with technology backgrounds. Interestingly, financially motivated investors also show a negative correlation with a professional background in finance. This may be an indicator of a possible “hype effect” surrounding ICOs. Financially motivated ICO investors appear to have neither a technological nor a financial background, invest only small amounts of money in several ICOs, are more afraid of fraud, and may target short-term profit. The short-term investment horizon of these investors is also reflected by the relatively high factor loading of “future sale of the token shortly after the ICO” on financial motives (Table 5.2). In other words, this indicates that the ICO market may be driven by herding behavior to some extent, similar to the context of crowdfunding (Ante et al., 2018; Vismara, 2016; Vismara, 2018). Similar to crowdfunding, ICOs are shown prominently in media, which may lead to social contagion processes. These financially oriented ICO investors may simply follow others, without considering all the facts, such as reading white papers, or their own (financial) background and aim at high-profit margins (e.g., Simonsohn and Ariely, 2008).

5.5 Conclusion

5.5.1 Discussion

A feature of ICOs is that investors follow ideological motives when investing in them. This notion may differentiate ICOs from more traditional forms of entrepreneurial finance such as venture capital. However, there is a parallelism with crowdfunding and its potential to democratize finance in terms of providing financing and investment opportunities (Cumming et al., 2019b). While the prior crowdfunding research has not focused on assessing or depicting ideological investor motivations in detail, several studies mention personal, ideology-driven investor motives (e.g., Gerber and Hui, 2013). In contrast to crowdfunding research, however, our findings indicate that ideological motives play a role in the ICO context. Supporting our findings, recent evidence has suggested that shared ideologies are among the drivers of the diffusion of Bitcoin (Bogusz and Morisse, 2018).

This finding parallels the research in the domain of open-source software. Henkel (2008) and Lakhani and Wolf (2005) show that a “free software ideology” is a similarly important driver in the development of software. Stewart and Gosain (2006) develop a framework for the “open source software ideology” and show that adherence to this ideology has crucial implications for the effectiveness of development teams. The notion of open source is also present in ICOs, in which revealing source code is a de facto standard that the majority of ventures follow (Fisch, 2019).

Additionally, our findings resemble those of the entrepreneurship research on founder identities. Building on social identity, Fauchart and Gruber (2011) identify the existence of three basic types of founder identities that shape an individual’s funding decisions and have a major impact on the entrepreneurial process. In particular, they distinguish Darwinian identities (i.e., traditionally business-oriented and focused on profitability), communitarian identities (i.e., motivated by the interest of a community), and missionary identities. They describe that missionary founders believe that firms can be powerful agents of social change and are mainly motivated by founding a company with a particular mission (e.g., political, social, or environmental). Hence, ideological motives seem to play an important role not only for founders but also for providers of entrepreneurial finance.

5.5.2 Implications for theory and practice

From a theoretical perspective, our exploratory findings primarily contribute to the nascent research on ICOs (e.g., Ante et al., 2018; Fisch, 2019; Huang et al., 2019). Our study is the first to assess this topic from the perspective of ICO investors and identifies a nuanced set of investment motives, which is crucial to understanding and interpreting the increase in ICOs and the associated economic effects. In addition, our descriptive statistics and analyses enable us to profile ICO investors. Most importantly, it seems to be very difficult to identify average ICO investors, as the heterogeneity among investors is considerable.

Our findings further and more generally contribute to the research in entrepreneurial finance. We extend the prior research, mainly in the related domain of crowdfunding (e.g., Gerber and Hui, 2013; Allison et al., 2015), to the context of ICOs by showing that ICO investors are similarly motivated by intrinsic and extrinsic motives. Speaking to the relative importance of the criteria, our results further show that ICO investors consider intrinsic motives to be more important than extrinsic motives. This finding has interesting implications and indicates that ICOs are not yet seen as a purely financial investment. An explanation for this might be that professional financial investors have not yet started to adopt ICOs as an investment vehicle because of their novelty, the high risk involved, and/or the strong technological component. It will be interesting to see whether extrinsic motivations become more important as ICOs gain more widespread adoption.

Relatedly, the research on crowdfunding often assumes that the average crowdfunding investor makes small contributions and is a less experienced investor (Schaef et al., 2018). Similarly, anecdotal evidence suggests that the average sum invested in ICOs is indeed relatively low (e.g., Lympo, 2018), while some sources suggest a simultaneously high degree of centralization in the distributions of tokens (e.g., Azaraf, 2018). It is also unclear whether ICOs can be characterized as being funded by novice investors. Recent evidence has suggested that institutional investors, who are typically more professional than private investors, seem to have begun to invest in ICOs (Kastelein, 2017; Kharif and Russo, 2018). Our results indicate that ICO investors do not necessarily make small donations or are not necessarily inexperienced.

The understanding of the investment motives in ICOs is of major importance for policymakers dealing with financial inclusion. Because of its novelty and the significant differences in regulation between countries, more research is needed to understand how this investment vehicle will alter the process of entrepreneurial financing. Recently, Cumming et al. (2019a) have examined a large body of public comments submitted by stakeholders in response to the new equity crowdfunding regulations proposed by the SEC in 2013. The protection of small investors investing alongside sophisticated investors has been found to be a primary concern for regulators and public commenters. Hornuf and Schwienbacher (2017) point out that the appropriateness of the regulation for new forms of early-stage finance is contextually determined by the availability of traditional early-stage financing alternatives, such as business angels and venture capitalists. Although ICOs provide entrepreneurs with less costly access to external financing because of the loose regulatory setting and limited accreditation standards, Huang et al. (2019) find that a well-developed digital regulation environment is more likely to accommodate the special needs in the ICO market. Accordingly, the evidence from our study points to the need to tailor the level of regulation according to the types of investors. A uniform regulation regarding ICOs may not be equally attractive to and protect all types of ICO investors. While stricter regulation is not necessary for ideological investors, it is required by investors motivated by the prospects of financial returns. As such, our findings can serve as the cornerstone for a more fine-grained approach to developing policies that take into account the differing sets of investment motives. This is especially important since ICO policymaking is still in its early stages, in which overly general regulation might severely undermine the innovative potential of ICOs. This carries important ecosystemic consequences, as a fine-grained regulated digital economy is more likely to encourage start-ups to propose and generate new digital services and business models, as it reduces systemic risk.

Our findings also inform ICO-conducting ventures that there is considerable heterogeneity among investors with regard to why they invest in ICOs. Blockchain entrepreneurs, therefore, need to structure their campaigns differently if they want to attract different sets of investors. We argue, for instance, that white papers are more important to technologically motivated investors. The highlighting of the utility function of tokens or the societal goals of the projects, such as their sustainability or philanthropy, will attract ideologically motivated investors. This, however, might cause investors who rate financial motives as being most important to miss out. To attract such types of investors, entrepreneurs should highlight the scalability of their business models since financially motivated investors typically aim to cash out quickly. Finally, ventures that are trying to appeal to a broad set of investors should make sure to cater to this broad set of motives when trying to attract funding.

5.5.3 Limitations and future research

This study is not without limitations. One set of limitations refers to our survey methodology. First, we rely on self-selection sampling. While we tried to spread the questionnaire across different outlets to obtain a diverse set of responses and while we performed a late-response test, we cannot rule out the potential for our study being affected by sampling bias. We are not aware of any other study that focusses on or surveys ICO investors, so there are no other findings that we could compare our results to assess potential bias. Second, our survey was conducted between June and August 2018. Because the ICO sector is fast-paced, we cannot rule out that the behavior of investors has changed considerably since 2017. The high value of risk-taking in our sample might be influenced by the fact that risk-averse investors already left the market by mid-2018 after the market considerably declined. Similarly, we do not know whether our findings can be generalized to future ICO investors, as the composition and motives of ICO investors might change in the future. Future studies might thus draw different samples or larger samples or repeat our investigation to see whether motives and investor profiles change.

Furthermore, our study cannot uncover or investigate causal relationships. While our regression analysis provides an initial approach to profile investors, more sophisticated approaches are necessary. For example, future research could investigate differences across respondents in a more theory-driven way by building upon our findings and trying to validate our findings using methods that allow for greater causal inferences. Relatedly, our set of investor motives is based on SDT and the prior research in the domain of crowdfunding. However, our items to capture these motives may not encompass all existing investor motivations. Additionally, the internal consistency of our factors is not very high. Thus, future research could build on our motivations and identify further motives of ICO investors. For example, qualitative approaches may be particularly suitable to uncover such motives. Also, it would be interesting to assess the relationship between investment motives in ICOs and those in other means of entrepreneurial finance. For example, a nuanced comparison of investment motives among ICOs, crowdfunding, and venture capital investments could provide interesting and novel insights. Such a comparison of investors could provide important insights into the complementarities and differences between various forms of entrepreneurial finance.

Additionally, we assess ICO investors that are isolated from the ventures in which they invest. However, the characteristics of the investment target are likely to influence an individual's investment behavior. The understanding of how investment motives and target selection interact is crucial to fully understand the ICO process. Future research should thus try to combine data on ICO ventures, which have been frequently used in past studies, with data on investors. A matched dataset of ventures and investors could enable a significantly improved understanding of ICOs.

Finally, different investment motives might coincide with a preference for different token types (Fisch, 2019). For example, ICO investors mainly driven by technological motives might tend to invest in utility tokens that they can later use. In contrast, financially motivated investors might tend to invest in security tokens, as they are tied more directly financial benefits. While we did not capture whether investors primarily invest in a specific token type, a deeper investigation of the interrelationships between token types and investment motives provides an avenue for future research.

5.6 Appendix

Table 5.A1: Assessing a potential late response bias

	(1) Early respondents (N = 129)	(2) Late respondents (N = 129)	t-test (1) vs. (2)
Investment motives	**Mean**	**Mean**	
Personal enthusiasm for the technology	4.26	4.10	0.16
Personal enthusiasm for the business model/idea	4.22	4.16	0.06
Future sale of the token shortly after the ICO	3.02	3.12	-0.11
Future sale of the token at a later point in time	4.28	4.17	0.11
Gaining an equity stake in the ICO venture	3.05	3.05	0.00
Financial gains	3.58	3.59	-0.01
Use tokens in their intended utility function	3.61	3.32	0.29*
Social motives	3.05	2.69	0.36**
Disrupting established structures/industries	4.00	3.84	0.16

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5.A2: Correlations and variance inflation factors (VIFs)

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**	**(21)**	**VIF**
Motives to invest																						
(1) F1: Ideological																						1.12
(2) F2: Technological	0.00																					1.08
(3) F3: Financial	0.00	0.00																				1.11
Sociodemographics																						
(4) Age	-0.06	**0.09**	-0.03																			1.18
(5) Gender	**-0.09**	-0.05	-0.02	-0.01																		1.07
(6) Residence: US	0.03	0.08	-0.01	0.05	-0.04																	1.32
(7) Residence: EU	-0.05	-0.06	**-0.14**	0.05	**0.10**	**-0.44**																1.41
(8) Risk-taking	-0.07	**0.11**	0.05	**-0.09**	0.07	0.00	-0.05															1.12
(9) Level of education	-0.06	-0.01	-0.04	**0.11**	0.05	0.00	0.05	-0.02														1.10
(10) Edu: Business	-0.02	-0.03	**-0.09**	0.06	-0.02	-0.03	0.06	0.07	**0.11**													1.43
(11) Edu: Comp. sci.	0.07	0.05	-0.02	0.03	0.08	0.01	0.00	-0.06	-0.05	**-0.38**												1.52
(12) Occ: SE	-0.02	0.01	0.03	**0.19**	0.01	0.03	**-0.12**	**0.09**	0.08	0.07	-0.04											2.65
(13) Occ: Employee	0.04	0.05	-0.07	0.02	0.00	0.03	0.07	-0.06	0.04	-0.02	0.04	**-0.74**										2.46
(14) Prof: Technology	-0.01	-0.03	**-0.12**	0.00	0.07	0.02	0.00	**0.09**	0.04	**0.42**	-0.21	**0.11**	-0.06									1.40
(15) Prof: Finance	**0.11**	0.00	-0.04	0.05	-0.03	-0.03	-0.02	-0.05	-0.07	**-0.30**	0.51	-0.06	0.10	**-0.34**								1.56
(16) Inv. Knowledge	0.08	**0.09**	-0.05	0.08	-0.04	0.07	**-0.18**	**0.20**	**0.15**	**0.19**	-0.07	**0.16**	-0.08	**0.25**	-0.07							1.28
ICO investments																						
(17) First investment	**0.14**	0.03	-0.07	0.02	0.01	0.00	-0.01	0.06	-0.01	**-0.10**	0.03	0.04	-0.01	-0.02	0.02	0.08						1.11
(18) No. of ICO inv.	-0.01	0.01	0.04	0.07	0.01	**-0.11**	-0.07	**0.13**	0.02	0.04	-0.01	0.16	**-0.11**	0.06	0.00	**0.10**	**0.15**					1.63
(19) Inv. ($)	0.00	0.04	-0.06	**0.14**	0.08	-0.05	-0.07	**0.14**	0.05	0.02	-0.01	0.24	**-0.16**	0.08	-0.03	**0.17**	**0.22**	**0.60**				1.74
(20) Afraid of fraud	0.08	-0.02	**-0.12**	-0.05	0.06	-0.02	0.08	0.01	-0.06	0.04	0.03	0.01	-0.02	0.05	-0.05	-0.07	0.02	**0.10**	**0.09**			1.13
(21) Need regulation	-0.01	0.00	**0.10**	0.02	0.00	**-0.17**	**0.14**	-0.04	**0.13**	0.05	-0.06	-0.10	0.08	0.04	0.02	0.08	**-0.10**	-0.05	-0.07	**-0.25**		1.19
(22) Read white paper	**0.19**	**0.19**	0.01	0.01	-0.07	0.05	**-0.09**	0.06	0.02	0.02	0.03	0.10	-0.05	0.07	-0.01	**0.18**	0.02	0.02	**0.09**	0.01	0.04	1.13

Notes: N = 517. Significant coefficients (p < 0.05) in bold.

Chapter 6

Venture capital and the performance of blockchain technology-based firms (BTBFs): evidence from ICOs

Initial coin offerings (ICOs) represent a novel mechanism of entrepreneurial finance that blockchain technology-based firms (BTBFs) use to raise capital. While venture capital (VC) plays a crucial role in the financing of innovative ventures, little is known about the role of VC in ICOs. To address this research gap, we hand-collect data on VC participation for a comprehensive sample of 2,905 ICOs. We assess BTBF post-ICO performance in terms of growth, utilization, and profitability and employ econometric methods to control for the endogeneity inherent in VC financing. Our results suggest that VC financing causes BTBFs to substantially outperform their peers. Specifically, we find that VCs are not able to pick better BTBFs to invest in (selection effect). Instead, they add value post-invested (treatment effect). Further analyses show that VC financing positively affects other ICO outcomes (e.g., funding amount, ICO duration, and exchange listings). Overall, we show that VCs are an important, value-increasing intermediary in the emerging blockchain sector. Our findings have profound implications for research on ICOs and VC, as well as for BTBFs, VCs, and policymakers.

This chapter is currently submitted to a journal.

6.1 Introduction

Initial coin offerings (ICOs) or, synonymously, token offerings, represent a novel mechanism of entrepreneurial finance that has substantially gained in popularity since 2017. ICOs enable ventures to raise capital by selling tokens to a crowd of investors (e.g., Fisch, 2019 [Chapter 4]; Momtaz, 2019b). Tokens are cryptographically protected digital assets implemented on a blockchain, which is a novel approach to recording and transmitting data across a network in an immutable manner (Li and Mann, 2018; Natarajan et al., 2017). Blockchain technology is required for issuing and selling tokens and is at the core of token-based business models. Therefore, we refer to these ventures as blockchain technology-based firms (BTBFs).

Blockchain technology is a potentially revolutionary and disruptive technological innovation with vast potentials (e.g., Swan, 2015; Yermack, 2017). The funding of ventures building on such innovative technologies is among the premier topics in entrepreneurial finance and receives high attention from both theory and practice (Block et al., 2018a; Fisch et al., 2019 [Chapter 5]). Indeed, the acquisition of financial resources is a key challenge for entrepreneurial ventures that often have difficulty attracting financing because of high uncertainty, information asymmetry, and asset intangibility. Prior research shows that venture capital (VC) plays a crucial role in overcoming these challenges and financing innovative ventures (e.g., Baum and Silverman, 2004; Bertoni et al., 2011; Cochrane, 2005; Colombo and Grilli, 2010; Gompers and Lerner, 2001).

Venture capitalists (VCs) deliberately invest in emerging high-growth markets and focus on new technologies (e.g., Rosenbusch et al., 2013; Zacharakis et al., 2007). Hence, the blockchain sector should be particularly prone to VC investments. Supporting this notion, Huang et al. (2019) describe that VC funds invest high amounts in new digital finance markets. This is supported by a plethora of anecdotal evidence suggesting that VCs increasingly engage in ICOs to finance BTBFs (e.g., Kastelein, 2017; Kharif and Russo, 2018; Russell, 2018). In addition, industry reports indicate that investments by VCs in ICOs increased from 1.0 $b in 2017 to 3.9 $b in 2018. These include investments by renowned VCs like Sequoia Capital and Andreessen Horowitz, which each participated in deals exceeding 100 $m in 2018 (Diar, 2018).

In spite of this initial evidence, little is known about the role of VCs for the financing of BTBFs and their participation in ICOs. However, understanding how and whether experienced institutional investors participate in this novel market is crucial for BTBFs seeking financing, financial intermediaries, and policymakers. Specifically, understanding VC investments in BTBFs via ICOs is crucial for an evidence-based evaluation of the development and significance of the blockchain sector from an economic perspective. To fill this research gap, we seek to answer the following research question: How does VC financing influence BTBFs' post-ICO performance?

To answer this research question, we hand-collect data on VC participation for a comprehensive sample of 2,905 ICOs. We are able to obtain post-ICO performance data for more than 500 BTBFs. Since we are mainly interested in the causal effect of VC financing on BTBF performance, we employ a restricted control function approach to deal with the endogeneity of VC participation and performance (cf., Bertoni et al., 2011; Colombo and Grilli, 2010). That is, we disentangle the effect that VCs may be able to select BTBFs that would achieve superior performance regardless of VC involvement (selection effect) from the effect that VCs may be able to differently influence BTBF post-ICO performance due to superior coaching abilities (treatment effect). Our empirical results show that VC-backed BTBFs have a statistically and economically significantly higher post-ICO performance. Specifically, we find that the growth rates of BTBFs' market capitalization (proxy for growth), token liquidity (proxy for utilization), and buy-and-hold returns (BHR) (proxy for profitability) are substantially higher for VC-backed BTBFs. Our results also show that this increase in performance is due to a treatment effect instead of a selection effect. Further analyses show that VC financing positively affects other ICO outcomes (e.g., funding amount, ICO duration, and exchange listings). Overall, our results suggest that VCs are an important, value-increasing intermediary in the emerging blockchain sector.

Our contribution to theory and practice is twofold. First, we contribute to the nascent research on ICOs. Existing empirical studies mainly investigate the determinants of ICO success (e.g., Adhami et al., 2018; Fisch, 2019; Howell et al., 2018; Momtaz, 2019a) and post-ICO investor returns (e.g., Benedetti and Kostovestky, 2018; Lyandres et al., 2018; Momtaz, 2018). We add to this research by showing that VC financing substantially affects BTBFs' post-ICO performance, which we attribute to VCs' ability to professionalize portfolio firms. Thus, our findings introduce VCs as another important player in the ICO-sphere, whose presence future studies need to account for. For practitioners, this finding has important implications as it informs BTBFs that trying to attract VCs, rather than relying solely on the participation of a crowd of retail investors, may have a profound effect on the success of their business.

Second, we contribute to prior research on VC investments in entrepreneurial finance (e.g., Baum and Silverman, 2004; Colombo and Grilli, 2005; Rosenbusch et al., 2013). Our findings extend this established research to the novel context of ICOs. Specifically, our research contributes to the important sub-stream of research that disentangles selection from treatment effects (e.g., Bertoni et al., 2011; Colombo and Grilli, 2010). In line with prior research in other sectors, we show that VCs do not possess superior selection abilities, but add value to their portfolio companies post-investment. This informs research that distinguishing selection and treatment effects is crucial to coherently contextualize the effect of VCs and derive valid conclusions. Additionally, the public trading of tokens after an ICO gives us access to daily data of market capitalization, liquidity, and returns, which, in turn, can yield novel insights into the long-standing question of how VC financing affects venture performance (e.g., Davidsson et al., 2009). We show that VCs' impact is not only visible in terms of BTBF growth, but also in terms of profitability and utilization, underlining the profound benefits of attracting VCs for BTBFs. Simultaneously, our findings inform VCs that the blockchain sector may be an attractive market segment in which they can add value. In addition, our findings inform policy-makers trying to regulate ICOs that stimulating VC investments in ICOs can help accelerate BTBF performance. Traditional investors often dislike regulatory uncertainty (Kastelein, 2017), so that reducing regulatory uncertainty may be key in stimulating VC activity. Our findings inform policy-makers that incentivizing or facilitating VC participation may be beneficial to realize the technological potentials and long-term survival of this market.

6.2 Conceptual framework and predictions

6.2.1 The relationship between VC and venture performance

Prior research documents a positive relation between VC financing and portfolio venture performance (e.g., Baum and Silverman, 2004; Chemmanur et al., 2011; Rosenbusch et al., 2013). For example, Puri and Zarutskie (2012) find that VC financed ventures suffer from lower failure rates and have a higher performance than ventures without VC financing. Similarly, Kaplan and Lerner (2010) estimate that roughly 60% of the IPOs by entrepreneurial ventures between 1999 and 2009 were VC-financed. This ratio is disproportionally high, as only 0.2% of all ventures received VC. The success of VC financing is usually attributed to two factors:

(1) Selection effect (scouting function). VCs seek to invest in portfolio firms with a high potential for growth (e.g., Hoenig and Henkel, 2015; Puri and Zarutskie, 2012). This is because high returns for VCs are easier to achieve in scalable ventures (e.g., Cochrane, 2005). Hence, a positive association between VC financing and venture performance could be explained by VCs' ability to select portfolio companies with a higher future performance (e.g., Baum and Silverman, 2004; Bertoni et al., 2011; Rosenbusch et al., 2013). Conceptually, this research mainly draws on signaling theory (Spence, 1973) as well as resource-based arguments (e.g., Manigart et al., 1997). Since the quality of a start-up often cannot be observed directly, VCs have to rely on other sources of information, in particular on observable characteristics of the new venture (e.g., Hoenig and Henkel, 2015; Stuart et al., 1999). Therefore, VCs spend a substantial amount of time and effort on assessing these signals to infer the underlying quality of ventures they seek to invest in.

(2) Treatment effect (monitoring/guidance function). In addition to providing financial resources, VCs contribute to portfolio firm performance by offering bundles of value-adding services (e.g., Baum and Silverman, 2004; Chemmanur et al., 2011). These value-adding activities are multifold and include various corporate activities such as providing professional coaching and enabling access to the VCs' networks (e.g., Bertoni et al., 2011; Hellmann and Puri, 2002; Puri and Zarutskie, 2012). For example, Cumming et al. (2005) argue that VCs can add value by providing expertise (e.g., in the domains of finance, marketing, administration, and strategy/management). Hellmann and Puri (2002) focus on VCs' impact on the professionalization of portfolio firms' HR practices. They find that VCs tend to make substantial changes to firms' organization structures by replacing founders or hiring marketing and sales executives, introduce stock option plans, and formulate HR policies. Sapienza et al. (1996) show that VCs rate their strategic involvements (i.e., providing financial and business advice) as most important, followed by their interpersonal roles (i.e., as a mentor) and the access to their network. Finally, Hsu (2004) provides evidence that VCs' non-financial services may be more important to portfolio firms than the financial capital they provide.

6.2.2 Predictions

Conceptually, the positive association between VC financing and venture performance is explained by selection and treatment effects. Extending resource-based and uncertainty-based arguments to the context of ICOs, we argue that VC financing should be positively associated with BTBF performance. Specifically, we argue that this positive association is mainly driven by a treatment effect, whereas a selection effect is ambiguous.

Prediction 1: Ambiguous selection effect of VC financing on BTBF performance

Prior research argues that a positive association between VC financing and venture performance can be explained by VCs' ability to select portfolio companies with high future performance (e.g., Baum and Silverman, 2004; Chemmanur et al., 2011).

The explanation for this positive selection effect follows a resource-based logic. VCs devote considerable resources to evaluating and screening investment opportunities, for example, by carrying out extensive due diligence and by implementing effective contracting (e.g., Colombo et al., 2019; Manigart et al., 1997; Kaplan and Strömberg, 2001; Gompers et al., 2016b). This resourceful and professional approach enables them to identify and subsequently invest in high-quality ventures. The professional investment selection is also one of the main factors as to why VC backing conveys a 'certification effect' to third parties. VC financing signals venture quality and certifies legitimacy to other potential resource providers (e.g., employees, suppliers, cooperation partners, financial intermediaries), facilitating further performance increases (e.g., Colombo et al., 2019; Gompers and Lerner, 2001; Hsu, 2004). VCs engaging in ICOs to invest in BTBFs will conduct similarly exhaustive due diligence to assess the quality of prospective portfolio firms. Hence, they should be able to distinguish ICOs of higher and lower quality.

However, findings on VCs' ability to identify and select high-performance ventures are inconclusive. Specifically, studies trying to disentangle selection and treatment effects majorly do not find evidence for a positive selection effect (e.g., Colombo and Grilli, 2005; 2010; Bertoni et al., 2011). Therefore, Bertoni et al. (2011) and Rosenbusch et al. (2013) conclude that VCs may not always be able to select the most promising ventures. These studies argue in two directions. On the one hand, a selection effect assumes that VCs are able to (1) identify and (2) invest in ventures with superior prospects. Even if VCs possess better screening abilities and can identify high-quality ventures, this does not imply that they are able to invest in them. In fact, Colombo and Grilli (2010) make room for the possibility that ventures with superior prospects self-select out of the VC market because they can obtain financing in other ways and without giving away part of their control. On the other hand, studies argue that the lack of a significant selection effect is due to the inherent uncertainty of the entrepreneurial context. Prior studies describe that uncertainty is particularly pronounced in the ICO context (e.g., Fisch, 2019; Huang et al., 2019), making the selection of high growth targets particularly difficult. In particular, the ICO context is characterized by a large degree of technological uncertainty. This is because the future development and adoption of blockchain technology are still unclear (e.g., Natarajan et al., 2017). Another source of uncertainty in the ICO context is the pronounced information asymmetry between ventures and investors (e.g., Fisch, 2019). For example, the amount of objective information available in ICOs is low due to the absence of formal disclosure requirements (e.g., Blaseg, 2018; Huang et al., 2019) and because ventures systematically bias information voluntarily disclosed in whitepapers (e.g., Momtaz, 2019a).

Taken together, while resource-based arguments suggest a positive selection effect, existing evidence suggests a non-existing and potentially negative selection effect, partly because high-potential ventures opt-out of the VC market and partly because of high uncertainty. Hence, we acknowledge that the net effect of VC selection on BTBF performance is ex-ante ambiguous.

Prediction 2: Positive treatment effect of VC financing on BTBF performance

In addition to financing, VCs provide their portfolio firms with value-adding activities that can lead to performance increases. This positive treatment effect of VC financing is well documented (e.g., Bertoni et al., 2011; Cumming et al., 2005; Puri and Zarutskie, 2012). Specifically, research prioritizing a sound disentanglement of selection and treatment effects conclusively shows that a positive association between VC financing and venture performance is mainly driven by this treatment effect (e.g., Colombo and Grilli, 2010; Bertoni et al., 2011).

The positive treatment effect is mainly explained by resource-based arguments. VCs provide their portfolio firms with resources they otherwise lack (e.g., Baum and Silverman, 2004; Rosenbusch et al., 2013). Specifically, prior research indicates that VCs can add more value to ventures in (very) early stages (e.g., Bertoni et al., 2011; Sapienza et al., 1996). This is because early-stage ventures often lack a lot of resources and are in greater need of coaching so that VCs are able to contribute more to their development. This argument can be extended to the ICO context since BTBFs engaging in ICOs are usually in very early stages and often do not yet have a developed project (e.g., Benedetti and Kostovetsky, 2018; Bussgang and Nanda, 2018; Fisch, 2019). Additionally, BTBFs are very technology-driven (e.g., Cohney et al., 2018; Fisch, 2019). Professionalizing their business model, specifically by adding business expertise that these ventures may otherwise lack, as well as introducing these ventures to VCs' business networks may thus be particularly salient.

Sapienza et al. (1996) also show that VCs' ability to add value is higher when uncertainty is high because VCs tend to increase their involvement in portfolio ventures with increasing uncertainty. For example, VCs increase the elaborateness of their governance mechanisms when uncertainty is high. In contrast, VCs' involvement will be lower when uncertainty is low since VCs adjust their level of monitoring to fit the perceived progress of the ventures (Sapienza et al., 1996). As mentioned above, the ICO context is characterized by considerable uncertainty. For example, this uncertainty affects BTBFs business models and proposed technologies, who are often in very preliminary development phases where their real-world applications or eventual success are very uncertain (e.g., Benedetti and Kostovetsky, 2018; Bussgang and Nanda, 2018; Fisch, 2019). Also, investors with limited technological expertise may find it difficult to understand the technology proposed by a venture (Fisch, 2019). To better understand their portfolio companies and help in developing them further, a close interaction between VCs and portfolio firms is likely.

Altogether, both resource-based and uncertainty-based arguments suggest a positive treatment effect of VC investments. Therefore, we expect the overall-predicted positive association between VC financing and BTBF performance to be mainly driven by VCs' abilities to add value (treatment effect).

6.3 Research design

6.3.1 Sample construction

We retrieve our core data from ICObench, a database that is commonly used due to its wide coverage (e.g., Huang et al., 2019; Lyandres et al., 2018; Momtaz, 2019a). We collected all ICOs with an announced issuance between August 2015 and December 2018. ICObench deletes failed ICOs from their databank, as do many other data sources. Where possible, we backfilled missing data with information retrieved from other sources such as CoinSchedule, Coingecko, and ICOalert. Using this iterative approach, we were able to identify an initial sample of about 4,000 ICOs.

Unfortunately, the information available is incomplete, which is a common problem in empirical studies on ICOs (e.g., Fisch, 2019). To mitigate data loss due to missing values and to collect additional variables of interest, we hand-collected further information from various sources such as project websites, Twitter, and GitHub. We also gathered historic price information from Coinmarketcap, which serves as the basis for our measures of BTBF performance and is the most established source for post-ICO performance data (e.g., Lyandres et al., 2018). To collect as much performance data as possible, we retrieved all data available until April 2019. Finally, we obtained data on VC financing from CryptoFundResearch, one of the most comprehensive databases on investments in the blockchain sector (as of May 2019).

After excluding entries with missing values, our final sample consists of 2,905 BTBFs that conducted an ICO, out of which 322 have successfully obtained VC financing. However, information on historical price data (main analyses) and information on the amount of funding (further analyses) was only available for 565 (189 VC-backed) and 1,081 (242 VC-backed) BTBFs, respectively.

6.3.2 Variables

Dependent variables: Venture performance

Venture performance is a multi-dimensional construct and is commonly operationalized in terms of profitability or growth (e.g., Davidsson et al., 2009; Wiklund, 1999). Research in entrepreneurship primarily focuses on growth. This is because new, innovative ventures need growth to achieve legitimacy and market survival and because reliable financial data on profitability is often not available for entrepreneurial ventures (e.g., Davidsson, 1991; Davidsson et al., 2009). Consequently, venture growth is also the most commonly used outcome variable in research on the relationship between VC financing and portfolio firm performance (e.g., Baum and Silverman, 2004; Bertoni et al., 2011; Rosenbusch et al., 2013).

In the context of BTBFs, multiple novel performance measures are available that enable nuanced insights into the impact of VC financing on different measures of venture performance. Prior research shows that the relationship between VC financing and performance strongly depends on how performance is measured (e.g., Rosenbusch et al., 2013). Therefore, assessing venture performance in multiple dimensions may enable more holistic insights into the relationship between VC financing and venture performance. We thus operationalize venture performance in three ways, using (1) market capitalization as a measure of growth, (2) token liquidity as a measure of business-model utilization (which is related to growth), and (3) buy-and-hold returns (BHR) as a measure of profitability. We collect our performance data from Coinmarketcap.

Growth. Growth is the main performance measure used in prior entrepreneurship research. As such, we use the growth in market capitalization over the first six months after the tokens' exchange listing date. This is a commonly used growth measure in the ICO context (e.g., Momtaz, 2018). Specifically, it is a suitable growth proxy as it measures day-to-day variation in BTBFs' market valuation, adequately reflecting the expectations VC and other investors.

Utilization (liquidity). As a performance measure unique to the ICO context, we measure platform utilization, which we capture via the growth in liquidity over the first six months after the tokens' exchange listing date. Cochrane (2005) points out that VCs are mainly interested in scalable platforms. A direct measure of platform scalability is liquidity because it measures the amount a specific token is used. The higher the growth in liquidity, the higher the growth in the customer base for a given BTBF. Howell et al. (2018) also assess liquidity, which they deem one of the most important measures of post-ICO performance.

Profits. To capture the effect of VC financing on BTBF profitability, we utilize buy-and-hold returns (BHRs) over the first six months of trading after the tokens' exchange listing date. Since VCs are financial investors interested in realizable returns, BHRs is a key measure for VCs and other investors. BRHs mimic the wealth gains for investors who purchased tokens on the first day and then sold them after sixth months of continuous token-holding. BHRs are frequently used as a performance measure in the IPO literature (e.g., Ritter and Welch, 2002).

Independent variable: VC financing

Our independent variable *VC Financing* is a dummy variable equal to one if a BTBF received VC, and zero otherwise. We undertook a great effort in constructing this variable, which is novel in the ICO context. Specifically, our initial data relies on a list of institutional investors and the ICOs they invested maintained by CryptoFundResearch. We extended these data by double-checking that ICOs not included in this list did indeed not obtain any VC by thoroughly checking their websites and social media channels.

Control variables: BTBF characteristics and ICO characteristics

We include a variety of control variables to rule out confounding influences. Our comprehensive list of control variables resembles those used in prior ICO research (e.g., Fisch, 2019; Momtaz, 2018, 2019a; Lyandres et al., 2018). The variables are obtained from ICO-compiling sites (e.g., ICObench), BTBFs' websites, and social media sites (e.g., Twitter).

The first set of control variables refers to BTBF characteristics that could potentially influence post-ICO performance (e.g., Momtaz, 2019a). These variables include the average of all expert ratings the venture received on ICObench at the time of the ICO. Ratings refer to the categories "team", "vision", and "product" (*Expert Rating*). Further, we include variables that capture whether the venture discloses its source code on the software platform GitHub (*GitHub*), whether the venture proposes to offer a new platform (*Platform*), and the number of distinct industries the venture aspires to serve (*# Industries*).

The second set of control variables refers to ICO characteristics that might influence post-ICO performance (e.g., Momtaz, 2019a). These variables include whether the token builds on the

Ethereum standard (*Ethereum*), whether a pre-ICO took place (*Pre-ICO*), the number of tokens created in the ICO (*Token Supply*), whether an airdrop was conducted to freely distribute a fraction of the tokens (*Airdrop*), whether the ICO offered a bounty program (*Bounty Program*), whether the ICO used a Know-Your-Customer (KYC) process or a whitelist (*KYC/Whitelist*), the number of Tweets by the venture during the ICO (*Twitter Activity*), and the number of ICOs with overlapping fundraising periods (*Competing ICOs*).

Finally, we include year dummies as well as industry dummies in all of our models.

Additional dependent variables used in further analyses

In additional analyses, we examine the effect VC backing has on the duration of the ICO in days (*ICO duration*), the amount of funding raised in the ICO (*Funding Amount*), and the number of token exchanges the token is listed on within 6 months after the ICO (*Listings*). These variables are in line with most prior studies on ICO success and enable deeper insights on how VC financing relates to measures of ICO success (e.g., Fisch, 2019).

All variables, their descriptions, and data sources are summarized in Table 6.1.

6.4.3 Method

Potential endogeneity in the independent variable

We are interested in the causal effect of VC on BTBF's post-ICO performance. However, prior research shows that deriving clear-cut causal evidence is challenging in this context. This is because the error term might be correlated with unobservable characteristics as well as with the dependent variable in an OLS regression of BTBF performance on *VC Financing*. This might be indicative of potential spurious correlation and reverse causality, respectively. For example, Bertoni et al. (2011, p. 1033) note in the context of new technology-based firms that "their growth performance is closely related to unobservable characteristics such as innovative business ideas, development of unique technology, or a team of smart owner-managers." If such unobservable characteristics affect BTBF performance and also affect the likelihood of obtaining VC financing, we might mistakenly conclude that VC-financing causes BTBF performance (spurious correlation). Moreover, if VCs are able to identify and invest in those BTBFs with better performance prospects, a significant coefficient on our independent variable may not indicate that VCs cause BTBF performance but the opposite (reverse causality).

Table 6.1: Description of variables and data sources

Variable	Description	Data Source(s)
Dependent Variables (Main Analyses)		
Growth in platform size	Growth in market capitalization (MktCap) over the first six months after the token's exchange listing date.	Coinmarketcap
Utilization (liquidity)	Growth in liquidity over the first six months after the token's exchange listing date.	Coinmarketcap
Profits	Buy-and-hold returns (BHR) over the first six months of trading after the token's exchange listing date.	Coinmarketcap
Independent Variable		
VC Financing	A dummy variable equal to one if a venture capital (VC) fund invested in the venture, and zero otherwise.	Crypto-Fund-Research, BTBF websites
Control Variables: BTBF Characteristics		
Expert Rating	The average of all expert ratings of the whole project at the time of the ICO	ICObench
GitHub	A dummy variable equal to one if the start-up discloses its source code on GitHub, and zero otherwise.	GitHub
Platform	A dummy variable equal to one if the start-up provides a new platform, and zero otherwise.	ICObench
# Industries	The number of distinct industries a start-up aspires to serve as a proxy for diversification.	ICObench
Control Variables: ICO Characteristics		
Ethereum	A dummy variable equal to one if the start-up uses a standard of the Ethereum platform such as ERC20, and zero otherwise.	ICObench
Pre-ICO	A dummy variable equal to one if a Pre-ICO took place prior to the actual ICO, and zero otherwise.	ICObench
Token Supply	The number of tokens created in the smart contract on the blockchain used in the token offering.	ICObench
Airdrop	A dummy variable equal to one if the project uses an airdrop to distribute at least a fraction of its tokens, and zero otherwise.	BTBF websites
Bounty Program	A dummy variable equal to one if the project has a bounty program in place, and zero otherwise.	BTBF websites
KYC/Whitelist	A dummy variable equal to one if the project used a Know-Your-Customer (KYC) process or a whitelist during the ICO.	ICObench
Twitter Activity	The number of Tweets by the start-up during the token offering.	Twitter
Competing ICOs	The number of token offerings with overlapping fundraising periods.	ICObench
Dependent Variables (Further Analyses)		
ICO Duration	Number of days between ICO's start and end.	ICObench
Funding Amount	Total gross proceeds raised in the ICO (in $m).	ICObench, BTBF websites
Listings	Number of token exchanges a token is listed on within 6 months after ICO ends.	ICObench, BTBF websites

To overcome these methodological challenges, we employ a two-step restricted control function (rCF) approach following Heckman (1978, 1979) as well as Vella and Verbeek (1999), which has been applied previously in the context of VC-growth research (e.g., Bertoni et al., 2011; Colombo and Grilli, 2005, 2010). In a first step, we estimate a probit model that estimates the probability that a BTBF obtains VC financing. In a second step, we regress BTBF performance on *VC Financing* and controls, including a generalized residual obtained from the first stage to control for endogeneity in the VC variable.

Our approach is similar to related techniques used in prior research. Specifically, Bertoni et al. (2011) use a 10-year panel data set of Italian start-up firms to analyze how VC investments spur the growth in these firms using an augmented Gibrat law dynamic panel model, facing the same methodological issues as we do here. Given the recency of the emergence of BTBFs, we are not able to use time-series variation in addition to cross-sectional variation. Nevertheless, note that Bertoni et al.

(2011) conclude that the rCF approach yields precisely the same overall results as the dynamic panel method (i.e., VCs spur venture growth but are not able to select superior ventures). In light of this encouraging finding, we focus our empirical analyses on the rCF approach.[16] Additionally, we also control for sample selectivity and restrict our sample to matching BTBFs in robustness checks.

Selection model and performance model

We account for potential endogeneity using a two-step approach. In the first step, we estimate a selection equation that explains which BTBFs obtain VC financing and subsequently functions as a control for endogeneity. Hence, we employ a probit model and regress *VC Financing* on all control variables. The econometric rationale is that if VCs can identify and invest in future superior-performance BTBFs, the observable and unobservable characteristics driving BTBF performance should have a positive association with the probability of obtaining VC financing as well. This implies that the error terms in the selection and the performance models are positively correlated. In contrast, if there is no or a negative correlation among the error terms, a positive selection effect can be ruled out. In fact, a negative correlation might be indicative of future high-performance BTBFs purposely opting out of the VC market. One reason for such behavior is that, especially in thin VC markets, search costs for BTBFs are too high, and private information about growth prospects too favorable (Bertoni et al., 2011). To test for this, we compute the generalized residual from the first stage, which we include as a control variable in the second stage rCF regressions (Gourieroux et al., 1987).

In the second step, we estimate the effect of *VC Financing* on BTBF performance while accounting for potential endogeneity in the independent variable (captured via the selection model in the first step). Specifically, we regress our different measures of BTBF performance on *VC Financing*, the generalized residual, and a vector of controls. We employ an OLS model with robust standard errors as well as country and time fixed effects. Using this approach, a significantly positive coefficient of *VC Financing* and an insignificant or significantly negative coefficient of the generalized residual would indicate a positive treatment effect of VC finance and the absence of a selection effect.

[16] Note that related studies also sometimes employ an instrumental variable (IV) approach and estimate the probability of VC financing in the first stage and replace the VC dummy by the fitted values in the second stage. We abstain from this technique in the BTBF context. Most importantly, the IV estimate is only based on observables but, as Bertoni et al. (2011) point out, new technology-based start-ups cannot be well explained by observables. Especially in the context of BTBFs, data quality is a key challenge (Momtaz, 2019a). Additionally, Vella and Verbeek (1999) argue that estimates from the rCF approach are both, more efficient and more robust than IV estimates.

6.4 Empirical Results

6.4.1 Descriptive Statistics

Table 6.2 displays summary statistics for the full sample of 2,905 ICOs and for the subsamples for which performance data are available (# obs. between 541 and 610). Regarding our independent variable, 322 of the 2,905 ICOs (= 11.1%) obtained VC financing.

Dependent variables (performance measures). The BTBFs in our sample reach a mean market capitalization (proxy for growth) of 46.8 $m, liquidity (proxy for business-model utilization) of 1.96 $m, and buy-and-hold returns of 26.5% (proxy for profitability), six months after being listed.

Control variables: BTBF characteristics. We obtain expert ratings for all ICOs in our sample. Ratings scale from 0 (= weak) to 5 (= strong). The mean of all expert ratings over all ICOs is 3.15, with a standard deviation of 0.797. 88.1% of all BTBFs publish their code as open-source on GitHub. Of all sample BTBFs, the business idea of 56.7% is to provide a scalable platform, which on average is designed to serve 2.93 distinct industries.

Control variables: ICO characteristics. The Ethereum platform (e.g., ERC20) serves as the basis for 88.1% of all ICOs in our sample. More than half of the ICOs (51.2%) conducted a pre-ICO, and the overall token supply (log.) corresponds to 13.94 (i.e., 1.13 m tokens). This value varies a lot given the standard deviation is more than half of the average token supply (8.31). Regarding ICO promotions, 41.1% and 38.1% of all BTBFs choose to distribute tokens via airdrops and offer bounty programs to promoters, respectively. Less than one-quarter of all BTBFs (24.3%) require validation of their investors' identities via a KYC process or a whitelist. Twitter activity (log.) amounts to 4.84 with moderate variation (standard deviation of 1.51). Interestingly, the average token offering takes place in parallel to 282.9 competing ICOs.

Additional dependent variables used in further analyses (measures of ICO success). The average funding amount (13.9 $m) is very close to those reported in related ICO studies using different samples (e.g., Fisch, 2019). The average ICO duration is 59.4 days and 40.2% of all tokens are listed on exchanges.

Table 6.2: Descriptive statistics and correlations

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.
	# Observations	**541**	**610**	**565**	**2,905**	**2,905**	**2,905**	**2,905**	**2,905**	**2,905**	**2,905**	**2,905**	**2,905**	**2,905**	**2,905**	**2,905**	**2,905**	**1,081**	**2,905**	**2,905**
	Mean	**46.8**	**1.96**	**0.265**	**0.111**	**3.15**	**0.881**	**0.567**	**2.93**	**0.881**	**0.512**	**13.94**	**0.411**	**0.381**	**0.243**	**4.84**	**282.9**	**13.9**	**59.4**	**0.402**
	SD	**104.7**	**5.35**	**3.8**	**0.314**	**0.797**	**0.324**	**0.496**	**2.31**	**0.324**	**0.5**	**8.31**	**0.492**	**0.483**	**0.429**	**1.51**	**124.9**	**34.5**	**71.7**	**1.21**
1.	Growth																			
2.	Utilization	0.78																		
3.	Profits	0.34	0.37																	
4.	VC financing	0.36	0.27	0.06																
5.	Expert rating	0.07	0.06	-0.06	0.04															
6.	GitHub	0.09	0.05	-0.04	0.03	0.22														
7.	Platform	0.09	-0.02	-0.05	0.13	0.17	0.01													
8.	# Industries	-0.12	-0.09	-0.09	-0.08	0.25	0.03	0.35												
9.	Ethereum	0.05	0.04	0.00	0.02	0.04	0.02	0.02	-0.01											
10.	Pre-ICO	0.06	-0.03	-0.14	0.00	0.26	0.06	0.13	0.18	0.03										
11.	Token supply (log.)	-0.12	-0.03	-0.02	-0.21	0.25	0.06	0.03	0.16	0.00	0.12									
12.	Airdrop	-0.02	0.09	0.01	-0.07	0.34	0.04	0.06	0.16	-0.04	0.16	0.20								
13.	Bounty program	0.12	0.00	-0.11	-0.01	0.42	0.07	0.14	0.23	0.02	0.26	0.12	0.29							
14.	KYC/Whitelist	-0.11	-0.04	-0.09	-0.07	0.31	0.04	0.05	0.18	0.01	0.10	0.16	0.20	0.25						
15.	Twitter activity (log).	0.05	-0.04	-0.03	0.15	0.20	0.02	0.06	0.04	0.00	0.08	-0.03	0.10	0.08	0.07					
16.	Competing ICOs	-0.05	-0.06	-0.27	-0.05	0.18	0.09	0.05	0.18	0.07	0.67	0.15	0.17	0.25	0.13	0.00				
17.	Funding amount	0.09	0.09	-0.06	0.20	0.02	-0.07	0.05	-0.05	0.01	-0.01	-0.05	0.02	0.00	0.01	0.02	0.00			
18.	ICO duration	-0.12	-0.12	-0.06	-0.16	0.04	-0.03	-0.06	0.06	0.00	-0.04	0.08	0.08	0.06	0.03	0.03	0.06	-0.06		
19.	Listings	0.36	0.36	0.32	0.28	-0.06	-0.04	-0.05	-0.09	0.00	-0.14	-0.02	0.01	-0.11	-0.09	-0.03	-0.27	0.12	-0.11	

Table 6.2 also shows the correlations for all variables. No model specified below includes variables that have correlation coefficients higher than 0.42. All variance inflation factors (VIFs) are below 2.0. Both, correlation coefficients and VIFs are clearly below the commonly agreed thresholds so that multicollinearity does not seem to bias our results.

6.4.2 Main results on the effect of VC financing on BTBF performance

Effect on Growth

Table 6.3 displays our main results regarding the impact of VC financing on BTBF growth. Column (1) displays the selection model, column (2) the control model, and column (3) the performance (growth) model using the rCF approach. All models include country and year fixed effects as well as robust standard errors.

The selection model (column 1) predicts the likelihood that a BTBF obtains VC financing given a vector of observable characteristics in a parametrical specification using a probit model. The results show that many observable factors determine VC backing in the BTBF context. For example, the coefficient on *Expert Rating (avg.)* is significantly positive with a coefficient estimate of 0.3238. This implies that a one-standard-deviation increase over the average expert rating increases the probability of attracting VC financing by 58.2% (= 0.3238 + 0.3238 * 0.797). Platform-related business ideas also increase the likelihood of obtaining VC backing by 38.3%, while serving an additional industry reduces the odds of VC financing by 4.9%. Moreover, VC-backed BTBFs are less likely to conduct a pre-ICO (-19.8%), providing a higher token supply (-2.7%), and offering a bounty program for token promoters (-37.6%). Instead, VC-backed BTBFs are significantly more active in promoting their ICO on Twitter. No significant effects emerge regarding open source code on GitHub, Ethereum-based tokens, airdrops, KYC/whitelists, and the number of competing ICOs.

We then estimate inverse Mills ratios and generalized residuals (Gouriereux et al., 1987) and include these in the performance model (column 3) to account for the endogeneity of VC financing. We find highly significant effects. First, we document that the growth of VC-backed BTBFs exceeds the growth of non-VC-backed BTBFs by a rate of 9.36 ($p < 0.01$). Second, the results do not suggest that VCs are able to select BTBFs with better future growth prospects. Surprisingly, we actually find a significantly negative generalized residual, suggesting that VCs select BTBFs with relatively poor growth prospects. Overall, the evidence indicates that VC funds do not pick better BTBFs, rather they are able to develop them into outperformers.

Regarding the controls, we find that platforms, KYC/whitelists, and competing ICOs hurt BTBF growth, while increases in token supply and bounty programs positively affect BTBF growth. Note that the significances of the controls in column (3) differ from those in column (2). This implies that neglecting the existing endogeneity in market capitalization growth and VC financing produces substantially biased parameter estimates.

Effect on utilization (liquidity)

Table 6.4 uses platform utilization as the dependent variable. The results show that the utilization of VC-backed BTBFs exceeds that of non-VC-backed BTBFs by a rate of 13, suggesting that VCs are able to scale BTBFs to a level that drives the superior performance. Again, we document evidence of an existing endogeneity. Both the generalized residual and the inverse Mills ratio are statistically significant ($p < 0.01$). Also, the generalized residual is negative, supporting the previous finding that VCs are not able to pick better BTBFs. Instead, they seem to pick worse ventures to invest in. For the control variables, we find that platform solutions and competing token offerings hurt the liquidity increase after sixth months, whereas airdrops spur liquidity. It is also noteworthy that our model can explain between one-fifth and one-fourth of the variation in utilization growth (R^2).

Effect on profits (BHR)

Table 6.5 examines the effect of VC financing on BTBF profitability. The growth model (column 3) suggests that VC-backed BTBFs outperform non-VC-backed BTBFs by an economically and statistically significant rate of 41 ($p < 0.01$). Furthermore, we again find a significantly negative generalized residual. Among the control variables, platform solutions and competing token offerings negatively predict six-months BHR, while pre-ICOs have a positive effect.

6.4.3 Robustness tests

The combined results in Tables 3, 4, and 5 strongly support the view that VCs are not able to pick BTBFs with better performance prospects. Rather, they seem to develop BTBFs into industry champions. To ensure the robustness of these findings, we re-estimate all performance models (i.e., columns 3) using two alternative econometric approaches: Heckman's (1979) two-stage selectivity correction and propensity score matching (PSM) (e.g., Dehejia and Wahba, 2002).

The second stage of the Heckman model is presented in columns (4) of Tables 3, 4, and 5. It is identical to columns (3) with the exception that the generalized residual is omitted. This approach leads to three main findings. First, the coefficient of *VC Financing* is still significant and positive ($p < 0.01$), but its magnitude is decreased. Second, all control variables seem to be consistent with those reported for the rCF models in columns (3). Third, omitting the generalized residual results in partly significant losses in explanatory power (adjusted R^2).

Table 6.3: Main analysis of VC financing and growth in platform size

This table presents 2SLS regression results. Model (1) is the first-stage and regresses a dummy for VC financing on a vector of control variables. Model (2) regresses the second-stage dependent variable on all control variables to compare the parameter estimates of the controls to those in Models (3), (4), and (5). We address concerns about potential endogeneity in VC financing with Models (3), (4), and (5). Model (3) employs a restricted control function approach and includes the generalized residual as well as the Inverse Mills ratio as controls. Model (4) only includes the Inverse Mills ratio in the spirit of Heckman (1979). Finally, Model (5) replicates Model (4) with a propensity score-matched sample to further mitigate differences in the sample distributions of BTBFs that received VC financing and those that have not. Our second-stage dependent variable, Growth, is operationalized as the growth in market capitalization (MktCap) over the first six months after the token's exchange listing date. All variables are defined in Table 6.1. All models include robust standard errors. CF = control function. PSM = Propensity score matching. * p < 0.10, ** p < 0.05, *** p < 0.01

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Dependent variable	**VC financing**		**Growth in platform size**		
Model	**Probit**	**Control**	**Restricted CF**	**Heckman**	**PSM**
VC financing (dummy)			9.3599***	1.5698***	1.7539***
			(1.6464)	(0.2397)	(0.2991)
Generalized residual	*No*	*No*	*Yes*** (-)*	*No*	*No*
Inverse Mills ratio	*No*	*No*	*Yes****	*Yes****	*Yes***
Expert rating (avg.)	0.3238***	0.4240**	-0.4615	-0.5555	-0.5536
	(0.0609)	(0.1656)	(0.3695)	(0.3772)	(0.6524)
GitHub (dummy)	0.0931	0.1894	0.0921	0.2113	0.1875
	(0.1377)	(0.4161)	(0.3891)	(0.3970)	(0.6099)
Platform (dummy)	0.3825***	-0.0840	-0.7497**	-0.7928***	-0.8388*
	(0.0871)	(0.2421)	(0.2979)	(0.3044)	(0.5075)
# Industries	-0.0523**	-0.0747	-0.0083	-0.0410	-0.0489
	(0.0221)	(0.0795)	(0.0762)	(0.0776)	(0.1151)
Ethereum (dummy)	0.0493	0.1423	0.1059	-0.0130	-0.0213
	(0.1223)	(0.3327)	(0.3168)	(0.3229)	(0.4565)
Pre-ICO (dummy)	-0.1975*	0.2041	0.6872	0.9708**	0.6338
	(0.1196)	(0.3700)	(0.4261)	(0.4314)	(0.7239)
Token supply (log.)	-0.0267***	-0.0059	0.0376*	0.0514**	0.0513
	(0.0046)	(0.0132)	(0.0199)	(0.0202)	(0.0321)
Airdrop (dummy)	0.0097	0.5956**	0.3670	0.3117	0.2928
	(0.0856)	(0.2334)	(0.2287)	(0.2335)	(0.3358)
Bounty program (dummy)	-0.3761***	-0.1279	0.8719*	1.3183***	1.4547
	(0.1019)	(0.3291)	(0.4822)	(0.4836)	(0.9138)
KYC/Whitelist (dummy)	-0.0596	-0.3925	-0.5684*	-0.6016*	-0.5603
	(0.1032)	(0.3517)	(0.3317)	(0.3391)	(0.5147)
Twitter activity (log.)	0.1596***	0.0418	-0.0516	-0.2049*	-0.2490*
	(0.0276)	(0.0858)	(0.1075)	(0.1049)	(0.1448)
# Competing ICOs	0.0003	-0.0036**	-0.0037**	-0.0049***	-0.0041
	(0.0006)	(0.0017)	(0.0017)	(0.0017)	(0.0025)
Country/year fixed effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
No. observations	2,905	541	541	541	298
(McFadden) R2	(0.304)	0.215	0.310	0.274	0.312
Adjusted R2	-	0.128	0.231	0.192	0.195
p-value	0.000	0.000	0.000	0.000	0.000

Table 6.4: Main analysis of VC financing and platform utilization

This table presents 2SLS regression results. Model (1) is the first-stage and regresses a dummy for VC financing on a vector of control variables. Model (2) regresses the second-stage dependent variable, Utilization (Liquidity), on all control variables to compare the parameter estimates of the controls to those in Models (3), (4), and (5). We address concerns about potential endogeneity in VC financing with Models (3), (4), and (5). Model (3) employs a restricted control function approach and includes the generalized residual as well as the Inverse Mills ratio as controls. Model (4) only includes the Inverse Mills ratio in the spirit of Heckman (1979). Finally, Model (5) replicates Model (4) with a propensity score-matched sample to further mitigate differences in the sample distributions of BTBFs that received VC financing and those that have not. Our second-stage dependent variable, Utilization (Liquidity), is operationalized as the growth in liquidity over the first six months after the token's exchange listing date. All models include robust standard errors. CF = control function. PSM = Propensity score matching. * p < 0.10, ** p < 0.05, *** p < 0.01.

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Dependent variable	**VC financing**		**Platform utilization (liquidity)**		
Model	**Probit**	**Control**	**Restricted CF**	**Heckman**	**PSM**
VC financing (dummy)			13.0488***	1.9474***	2.0348***
			(1.9911)	(0.2867)	(0.2213)
Generalized residual	*No*	*No*	*Yes*** (-)*	*No*	*No*
Inverse Mills ratio	*No*	*No*	*Yes****	*Yes****	*Yes****
Expert rating (avg.)	0.3238***	0.7001***	-0.2875	-0.3412	-0.934*1
	(0.0609)	(0.2005)	(0.4115)	(0.4227)	(0.4852)
GitHub (dummy)	0.0931	0.3964	0.4298	0.5451	0.7833
	(0.1377)	(0.4951)	(0.4622)	(0.4745)	(0.4392)
Platform (dummy)	0.3825***	-0.3596	-1.1687***	-1.2062***	-1.7662***
	(0.0871)	(0.2879)	(0.3496)	(0.3591)	(0.3838)
# Industries	-0.0523**	-0.0767	0.0140	-0.0301	-0.0241
	(0.0221)	(0.0958)	(0.0912)	(0.0934)	(0.0860)
Ethereum (dummy)	0.0493	0.2775	0.2177	0.0411	-0.0815
	(0.1223)	(0.3840)	(0.3658)	(0.3744)	(0.3388)
Pre-ICO (dummy)	-0.1975*	0.0590	0.5566	0.8618*	1.2671**
	(0.1196)	(0.4476)	(0.4937)	(0.5041)	(0.5411)
Token supply (log.)	-0.0267***	-0.0084	0.0355	0.0530**	0.0872***
	(0.0046)	(0.0156)	(0.0223)	(0.0227)	(0.0238)
Airdrop (dummy)	0.0097	1.0595***	0.8673***	0.7619***	0.9731***
	(0.0856)	(0.2805)	(0.2730)	(0.2799)	(0.2509)
Bounty program (dummy)	-0.3761***	-0.4165	0.6430	1.1117**	1.7485**
	(0.1019)	(0.3930)	(0.5466)	(0.5550)	(0.6886)
KYC/Whitelist (dummy)	-0.0596	-0.1856	-0.4407	-0.4660	-0.4720
	(0.1032)	(0.4173)	(0.3923)	(0.4031)	(0.3840)
Twitter activity (log.)	0.1596***	-0.0881	-0.1628	-0.3619***	-0.5178***
	(0.0276)	(0.0992)	(0.1210)	(0.1189)	(0.1060)
# Competing ICOs	0.0003	-0.0035*	-0.0034*	-0.0049**	-0.0072***
	(0.0006)	(0.0021)	(0.0020)	(0.0020)	(0.0019)
Country/year fixed effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
No. observations	2,905	610	610	610	326
(McFadden) R2	(0.304)	0.151	0.257	0.212	0.247
Adjusted R2	-	0.0667	0.1798	0.1320	0.1319
p-value	0.000	0.001	0.000	0.000	0.000

Table 6.5: Main analysis of VC financing and platform returns

This table presents 2SLS regression results. Model (1) is the first-stage and regresses a dummy for VC financing on a vector of control variables. Model (2) regresses the second-stage dependent variable, Platform Returns, on all control variables to compare the parameter estimates of the controls to those in Models (3), (4), and (5). We address concerns about potential endogeneity in VC financing with Models (3), (4), and (5). Model (3) employs a restricted control function approach and includes the generalized residual as well as the Inverse Mills ratio as controls. Model (4) only includes the Inverse Mills ratio in the spirit of Heckman (1979). Finally, Model (5) replicates Model (4) with a propensity score-matched sample to further mitigate differences in the sample distributions of BTBFs that received VC financing and those that have not. Our second-stage dependent variable is operationalized as the buy-and-hold returns (BHR) over the first six months of trading after the token's exchange listing date. All models include robust standard errors. CF = control function. PSM = Propensity score matching. * p < 0.10, ** p < 0.05, *** p < 0.01.

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Dependent variable	**VC financing**		**Platform returns (BHR)**		
Model	**Probit**	**Control**	**Restricted CF**	**Heckman**	**PSM**
VC financing (dummy)			41.4050***	4.3011***	5.2027***
			(10.7693)	(1.5248)	(1.0009)
Generalized residual	*No*	*No*	*Yes*** (-)*	*No*	*No*
Inverse Mills ratio	*No*	*No*	*Yes***	*Yes***	*Yes****
Expert rating (avg.)	0.3238***	1.3559	-2.6353	-2.7134	-8.7187***
	(0.0609)	(1.0347)	(2.2280)	(2.2522)	(2.2127)
GitHub (dummy)	0.0931	-1.3114	-1.2679	-0.9180	3.6143*
	(0.1377)	(2.5570)	(2.5101)	(2.5354)	(1.9861)
Platform (dummy)	0.3825***	-2.3288	-5.1816***	-5.2664***	-9.6009***
	(0.0871)	(1.4767)	(1.8849)	(1.9053)	(1.7401)
# Industries	-0.0523**	0.0941	0.4225	0.2817	0.9739**
	(0.0221)	(0.4908)	(0.4911)	(0.4947)	(0.3876)
Ethereum (dummy)	0.0493	2.4229	2.1915	1.5546	2.5947*
	(0.1223)	(1.9706)	(1.9739)	(1.9868)	(1.5255)
Pre-ICO (dummy)	-0.1975*	4.2749*	6.2363**	7.3321***	10.7758***
	(0.1196)	(2.3055)	(2.6632)	(2.6733)	(2.4381)
Token supply (log.)	-0.0267***	0.0053	0.1682	0.2194*	0.5067***
	(0.0046)	(0.0809)	(0.1212)	(0.1216)	(0.1091)
Airdrop (dummy)	0.0097	2.8925**	2.1707	1.9054	1.6650
	(0.0856)	(1.4469)	(1.4805)	(1.4947)	(1.1421)
Bounty program (dummy)	-0.3761***	-1.0537	2.6868	4.2328	10.8508***
	(0.1019)	(2.0132)	(2.9420)	(2.9400)	(3.1183)
KYC/Whitelist (dummy)	-0.0596	-1.7428	-2.5376	-2.5450	-4.1368**
	(0.1032)	(2.1452)	(2.1204)	(2.1435)	(1.7334)
Twitter activity (log.)	0.1596***	-0.2378	-0.5505	-1.1526*	-2.1610***
	(0.0276)	(0.5271)	(0.6650)	(0.6491)	(0.5034)
# Competing ICOs	0.0003	-0.0430***	-0.0424***	-0.0477***	-0.0575***
	(0.0006)	(0.0106)	(0.0107)	(0.0107)	(0.0085)
Country/year fixed effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
No. observations	2905	565	565	565	319
(McFadden) R2	(0.304)	0.199	0.229	0.210	0.216
Adjusted R2	-	0.1123	0.1427	0.1228	0.0932
p-value	0.000	0.000	0.000	0.000	0.004

PSM results are displayed in columns (5) of Tables 3, 4, and 5. These models also go through the Heckman (1979) selectivity correction but are further restricted by the PSM to eliminate non-VC-backed BTBFs that do not sufficiently resemble VC-backed BTBFs. While we use a one-to-one nearest-neighbor probit matching model, the results are robust when using one-to-three and one-to-five nearest-neighbor matchings (not reported). The PSM results resemble those reported in column (4). Overall, however, the omission of the endogeneity-controlling generalized residual results in substantially understated effects of VC-backing on BTBF performance.

6.4.4 Additional analyses

Assessing long-term performance (12 months)

Our main analyses use performance data spanning 6 months after a tokens' listing. In an additional analysis, we extend this period and plot the development of growth, utilization, and profitability over a 12 months horizon for VC-backed and non-VC-backed BTBFs. Figures 6.2–4 graphically illustrate that VCs have a systematic and sustainable effect on BTBF performance.

Figure 6.1 shows the graphs for market capitalization (i.e., growth) and illustrates meaningful differences. VC-backed BTBFs have a higher market capitalization from the first day of trading. While the market capitalization remains relatively flat for non-VC-backed BTBFs, BTBFs with VC backing are able to realize constant growth. In fact, VC-backed BTBFs almost double their market capitalization within 12 months.

Figure 6.1: Growth of BTBFs with VC financing and without VC financing over the first 12 months after the token's exchange listing.

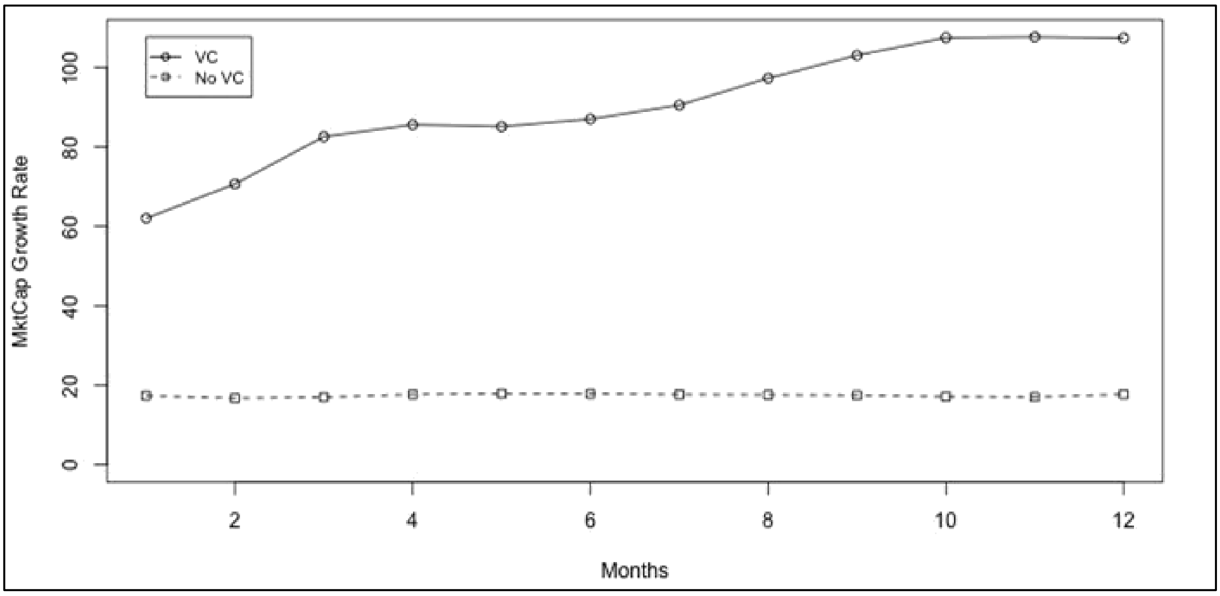


Figure 6.2 documents a similar pattern for liquidity (i.e., utilization). Again, non-VC-backed BTBFs show no growth in liquidity, while VC-backed BTBFs' utilization increases continuously. Interestingly, there is a strong increase in the growth rate in months 6 to 8, in which they realize most

of their liquidity increases. One explanation is that VCs help BTBFs to scale up their platforms via strategic growth initiatives that take a few months to materialize.

Figure 6.2: Platform utilization of BTBFs with VC financing and without VC financing over the first 12 months after the token's exchange listing.

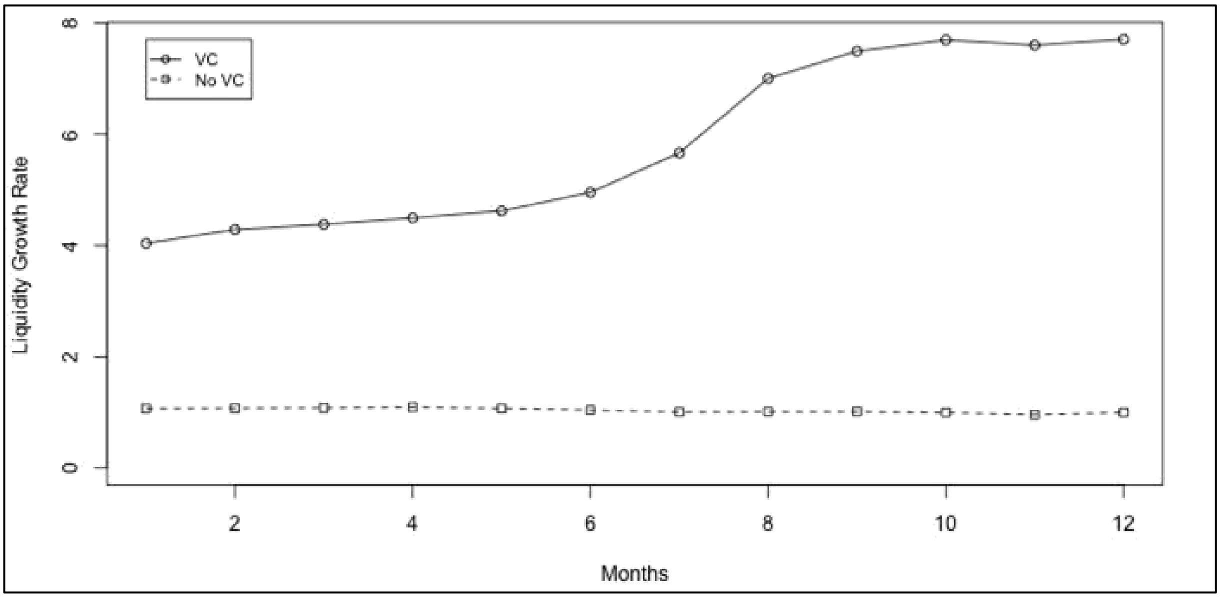
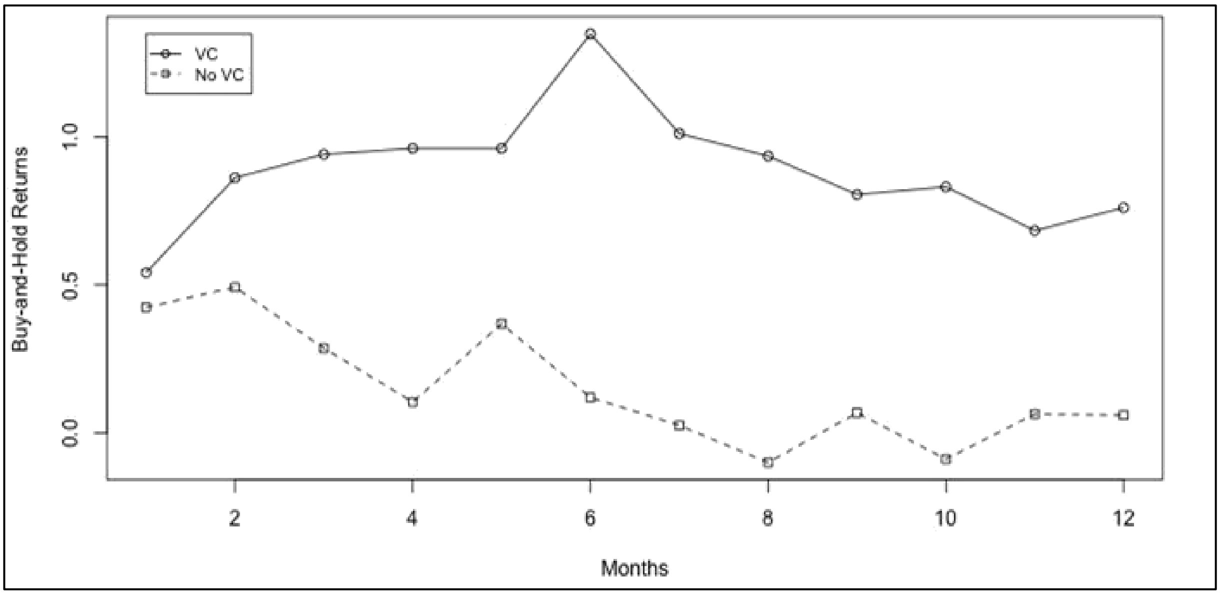


Figure 6.3 documents BTBF returns to investors (i.e., profitability) for VC-backed and non-VC-backed BTBFs. While return levels are similar in the beginning, after the second month, non-VC-backed BTBFs have decreasing returns to investors, which is consistent with the evidence reported for the universe of listed tokens on Coinmarketcap (Momtaz, 2018b). VC-backed BTBFs, which clearly perform better during the first 6 months, are able to maintain the profitability differential to non-VC-backed BTBFs.

Figure 6.3: Profits (BHR) of BTBFs with VC financing and without VC financing over the first 12 months after the token's exchange listing.



Impact of VC financing on measures of ICO success

Prior ICO research often focusses on the determinants of ICO success (e.g., Adhami et al., 2018; Fisch, 2019; Momtaz, 2019a). While VC financing likely plays a role in determining the success of an ICO, prior research has not accounted for this potential determinant. As a further analysis, we thus examine how VC financing affects the (1) funding raised in ICOs, (2) ICO duration, and (3) the number of exchanges tokens are listed on after the ICO. Table 6.6 shows the results. Our analyses follow the same approach as our main analyses. For the sake of brevity, control variables are omitted from Table 6.6.

Panel A of Table 6.6 shows that the presence of a VC in the ICO significantly increases the funding raised (i.e., VC-backed BTBFs raise 7.4 $m). The estimated effect is lower when we omit the generalized residual in columns (2) and (3) and instead rely on a Heckman correction and a PSM approach.

Panel B of Table 6.6 focusses on ICO duration in days (log.) as the dependent variable. VC financing is associated with a significant reduction in the time it takes a BTBF to complete the ICO. The parameter estimates for VC financing are again weaker in columns (2) and (3). Interestingly, the duration analysis is the only specification in which we observe a significantly positive generalized residual. This indicates that VCs invest preferably in those BTBFs that require less time-to-market, and are additionally able to further reduce the time-to-market.

Finally, panel C of Table 6.6 shows the results for the number of exchange listings (normalized) (log.). VCs play an important role in increasing the presence of their BTBF investments on token exchange listings. The finding may explain why VC-backed BTBFs experience significant increases in utilization since the additional exchange listings are related to access to new markets.

Overall, the results suggest that VCs play an important role in ICO success since VC-backed BTBFs are able to raise higher funding amounts in less time and are listed on more exchange platforms.

Table 6.6: Further analyses on the impact of VC financing on measures of ICO success

This table presents additional 2SLS regression results. Panel A uses log-transformed and normalized Funding Amount (in $) as the dependent variable. Panel B uses log-transformed and normalized ICO Duration (in days) as the dependent variable. Panel B uses log-transformed and normalized Number of Exchange Listings as the dependent variable. The first-stage model is omitted here for brevity, as it is identical to that reported in Tables 3 to 5. Model (1) employs a restricted control function approach and includes the generalized residual as well as the Inverse Mills ratio as controls. Model (2) only includes the Inverse Mills ratio in the spirit of Heckman (1979). Finally, Model (3) replicates Model (2) with a propensity score-matched sample to further mitigate differences in the sample distributions of BTBFs that received VC financing and those that have not. All models include the control variables described in Table 6.1 as well as country fixed effects and year fixed effects. All models include robust standard errors. CF = control function. PSM = Propensity score matching. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A. Effect of VC financing on funding amount

Column	**(1)**	**(2)**	**(3)**
Dependent variable	**Funding amount (log.) (normalized)**		
Model	**Restricted CF**	**Heckman**	**PSM**
VC financing (dummy)	2.0095***	0.7554***	0.7589***
	(0.7483)	(0.1022)	(0.0832)
Generalized residual	Yes*(-)	No	No
Inverse Mills ratio	Yes**	Yes***	Yes**
No. observations	1,081	1,081	901
R^2 (adj. R^2)	0.284 (0.236	0.282 (0.234)	0.533(0.506)
p-value	0.000	0.000	0.000

Panel B. Effect of VC financing on ICO duration

Column	**(1)**	**(2)**	**(3)**
Dependent variable	**ICO duration (log.) (normalized)**		
Model	**Restricted CF**	**Heckman**	**PSM**
VC financing (dummy)	-0.7013***	-0.2460***	-0.1987***
	(0.1109)	(0.0145)	(0.0127)
Generalized residual	Yes***(+)	No	No
Inverse Mills ratio	Yes	Yes	Yes
No. observations	2,901	2,901	2,263
R^2 (adj. R^2)	0.393 (0.378)	0.389 (0.375)	0.817 (0.813)
p-value	0.000	0.000	0.000

Panel C. Effect of VC financing on the number of exchange listings

Column	**(1)**	**(2)**	**(3)**
Dependent variable	**# Exchange listings (log.) (normalized)**		
Model	**Restricted CF**	**Heckman**	**PSM**
VC financing (dummy)	9.6766***	1.6636***	1.6881***
	(0.9522)	(0.1254)	(0.1073)
Generalized residual	Yes*** (-)	No	No
Inverse Mills ratio	Yes***	Yes***	Yes***
No. observations	2,905	2,905	2,263
R^2 (adj. R^2)	0.330 (0.314)	0.313 (0.297)	0.639 (0.631)
p-value	0.000	0.000	0.000

6.5 Discussion and concluding remarks

6.5.1 Discussion of the main results

We examine the causal effect of VC financing on the post-ICO performance of BTBFs. We mainly use measures unique to the ICO context to capture BTBF performance in a nuanced way. Specifically, we operationalize performance in terms of growth, utilization, and profitability. The potential endogeneity in our independent variable (*VC Financing*) poses an important methodological challenge. That is, it is ex-ante, not clear whether VC-backed BTBFs outperform non-VC-backed BTBFs because VCs are able to pick better targets (selection effect), or because VCs add value to the BTBF once they have invested (treatment effect), or both. To disentangle these potential effects, we follow Bertoni et al. (2011) and employ a rCF approach. In robustness tests, we also test sample selectivity correction models with and without PSM. The results are consistent across model specifications.

In particular, we find that VC-backed BTBFs seem to perform better because of the treatment effect, and not because of the selection effect. This finding is in line with prior research on new technology-based firms in Italy (e.g., Bertoni et al., 2011; Colombo and Grilli, 2010, 2005). The results suggest that distinguishing selection and treatment effects is crucial to understand the effect of VC on performance. Interestingly, our results, in fact, indicate a negative selection effect. A potential explanation is that BTBFs with great prospects self-select out of the VC market because they are able to raise sufficient funds independently and do not want to lose corporate control (Colombo and Grilli, 2010), although an empirical investigation of the detailed reasons for a negative selection effect is beyond the scope of this study. Altogether, our results indicate that VCs develop their portfolio firms into industry champions.

Additionally, our results indicate that VC financing also determines ICO success. Specifically, VC-backed BTBFs are able to raise significantly more funding in significantly less time, and their tokens are listed on more exchange platforms after ICO.

6.5.2 Contributions to Theory and Implications for Practice

The nascent body of research on BTBFs and ICOs has progressed rapidly since 2018. A major stream of empirical studies investigates the determinants of ICO success (e.g., Adhami et al., 2018; Fisch, 2019; Momtaz, 2019a; Howell et al., 2018). These studies identify multiple success factors in ICOs (e.g., technological characteristics, social capital, and human capital) that parallel factors identified for attracting VC (e.g., Baum and Silverman, 2004) or crowdfunding (e.g., Ahlers et al., 2015; Mollick, 2014). Another set of empirical studies assesses BTBFs post-ICO performance such as underpricing, short- and long-term returns, volatility, and liquidity (e.g., Momtaz, 2018; Benedetti and Kostovestky, 2018; Howell et al., 2018; Lyandres et al., 2018; Masiak et al., 2019). Other studies assess and evaluate ICOs from regulatory (Zetzsche et al., 2017), societal (Cohney et al., 2018), geographical (Huang et al., 2019), or investor and market sentiment perspectives (Drobetz et al., 2019; Fisch et al., 2019).

We contribute to this literature in two ways. First, our paper provides an initial assessment of the causal effect of VC financing on BTBF performance. The performance effect of VCs is particularly interesting due to the largely disintermediated character of blockchain finance. While blockchain technology was mainly developed to bypass financial intermediaries (Nakamoto, 2008), however, disintermediation may induce inefficiencies due to moral hazard and information asymmetries (Fisch, 2019; Momtaz, 2019a). Therefore, Momtaz (2018) argues that intermediaries may find substantial financial gains from eliminating such inefficiencies, which is in line with our findings. VCs' post-ICO impact is not only visible in terms of BTBF growth, but also in terms of returns to investors and token liquidity. In addition to increasing post-ICO performance, VCs also have a discernible impact on ICOs per se. Thus, our findings are crucial for future research in this area as they introduce VCs as another important player in ICOs and the blockchain sector more generally, whose presence needs to be accounted for.

Second, we contribute to prior research on VC investments in entrepreneurial finance (e.g., Baum and Silverman, 2004; Rosenbusch et al., 2013). Our findings extend this established research to the novel context of ICOs. Specifically, our research contributes to the important sub-stream of research that disentangles selection from treatment effects (e.g., Bertoni et al., 2011; Colombo and Grilli, 2010). While prior research often argues that a positive performance effect of VC investments is due to both selection and treatment effects, we show that a more nuanced view is necessary. In line with prior research in other sectors, we show that VCs do not possess superior selection abilities, but add value post-investment in ICOs. This finding attests to the importance of disentangling selection from treatment effects in order to coherently contextualize the role of VC involvement for start-up growth and to derive valid conclusions. Also, the public trading of tokens after an ICO gives us access to daily data of market capitalization, liquidity, and returns, which, in turn, can yield novel insights into the long-standing question of how VC financing affects venture performance. So far, this literature was confined to dependent variables such as sales growth and the number of employees due to a lack of other performance measures (e.g., Davidsson et al., 2009). Our more nuanced assessment underlines the large benefits of attracting VCs for BTBFs and informs prior research on the importance of considering different performance measures.

Additionally, our findings have important implications for practice. First, our findings inform BTBFs conducting an ICO that trying to attract VCs may have a profound and sustainable effect on the success of the ICO itself and post-ICO growth and performance. As such, entrepreneurs may consider tailoring and marketing their ICO in order to specifically appeal to VCs instead of relying solely on the participation of a crowd of unprofessional investors. This involves a careful trade-off between the benefits of VC backing and its costs (e.g., discounts on token prices and loss of control). Second, our findings inform policy-makers trying to regulate BTBFs and ICOs that stimulating VC investments in BTBFs can help accelerate start-up performance and reduce market frictions (Momtaz, 2019a). Traditional investors usually have a disutility from regulatory uncertainty (Kastelein, 2017), so that reducing regulatory uncertainty may be key in stimulating VC activity. So far, regulatory efforts have concentrated on establishing certain guidelines for individuals' participation in ICOs. Our findings suggest that incentivizing or facilitating VC participation may be key to realize the technological potentials and long-term survival of this market.

6.5.3 Limitations and avenues for further research

Our study is not without limitations. For example, we operationalize VC financing as a dummy variable, although other dimensions such as the investment amount and the specific involvement (e.g., operational coaching, board seats, etc.) promise additional insights. Unfortunately, we were not able to gather such information mainly due to the fact that most BTBFs and VCs do not yet disclose such information on their websites and established VC databases (e.g., Crunchbase) do not yet contain this information.

Other limitations relate to the external validity of our study. For example, performance measures are only available for a subset of our sample BTBFs. One reason is that not all BTBFs have listed their tokens yet; another reason is that the overlap between the different data sources we use is limited. We expect that both issues will fade with time as more and more data become available (in a standardized format). Another concern is that most data providers delete certain BTBFs from their records if they are unsuccessful. Also, while several data aggregators track ICOs, all of them have specific limitations. While we attempted to mitigate these issues in our data construction process, this is an issue in all studies on BTBFs and ICOs (see Momtaz, 2019a, for a thorough discussion).

Our findings open several promising avenues for future research. Future research could investigate VC involvement in a more nuanced way. Prior research shows that the timing of VC investments can be crucial and lead to information cascades (Vismara, 2018). VC investment in ICOs might similarly influence the dynamics of an ICO. Also, the reputation of VCs might moderate their influence on future performance. For example, Hsu (2004) shows that highly reputed VCs cause larger performance increases. Similarly, comparing the role of highly reputed VCs in ICOs to highly specified VCs (i.e., VCs that exclusively focus on the blockchain sector) might be an interesting avenue for research. Ex-ante, it is unclear which VC investments should be more beneficial to BTBFs.

VC investments typically involve syndication as investors rarely invest alone (e.g., Lerner, 1994; Manigart et al., 2006). One of the main reasons for syndication is to mitigate investment risk by spreading the risk to different parties. Since uncertainty is particularly high in the ICO context, institutional investors likely syndicate their investments. Extending the literature on syndication to the context of ICOs, and investigating the particularities of syndication in this novel context might be an extremely interesting topic for future research.

Finally, another stream of research deals with VCs' exit strategies (e.g., Cumming and Johan, 2008). While we show that VC financing leads to performance increases in BTBFs, we do not know whether VCs are able to successfully exit these ventures. However, an attractive exit option is a crucial prerequisite for VC investments. Indeed, ICOs are assumed to be more attractive to VCs since the possibility to trade tokens in secondary markets facilitates venture exist greatly (Bussgang and Nanda, 2018). An empirical investigation of returns to VCs in ICOs thus presents a logical extension to this study. Similarly, it appears equally interesting to study the consequences of VC departure for BTBFs.

Chapter 7

Conclusion

The final chapter of this postdoctoral thesis ("Habilitationsschrift") proceeds as follows: Section 7.1 outlines each chapters' main findings and provides brief answers to the main research questions addressed in this thesis. Section 7.2 summarizes the findings' main implications for theory and practice. Finally, Section 7.3 concludes the thesis by outlining avenues for future research.

7.1 Findings per chapter

This chapter outlines each chapters' main findings. Table 7.1 recapitulates the research questions addressed in this thesis.

Table 7.1: Research questions answered in this thesis

#	Research question	Answered in
RQ 1	*What are private equity investors' most important decision criteria and how does the importance attached to these criteria vary across investor types?*	Chapter 2
RQ 2	*How does personality influence business angels' decision to syndicate?*	Chapter 3
RQ 3	*What factors determine the amount of funding raised in initial coin offerings (ICOs)?*	Chapter 4
RQ 4	*What are ICO investors' motives to invest in ICOs, what is their relative importance, and how can ICO investors be profiled based on their motives?*	Chapter 5
RQ 5	*How does VC financing influence blockchain technology-based firms' post-ICO performance?*	Chapter 6

7.1.1 Chapter 2: Private equity investment criteria an experimental conjoint analysis of venture capital, business angels, and family offices

Chapter 2 assesses private equity (PE) investors' decision-making when investing in entrepreneurial ventures. To provide holistic insights on PE investors' investment decisions, we consider five different types of PE investors: family offices (FOs), business angels (BAs), venture capital funds (VCs), growth equity funds (GEFs), and leveraged buyout funds (LBOs). To answer RQ 1, we develop and conduct a large-scale conjoint analysis, in which investors were presented with a realistic investment decision scenario. Overall, we recorded 19,474 investment decisions by 749 private equity investors across the five different investor types.

The conjoint experiment allows us to assess the importance of investment criteria and to compare the importance attached to these criteria across investor types. Regarding the overall importance attached to different investment criteria, we find that PE investors consider (1) revenue growth, (2) value-added of product/service, and (3) management track record as the most important criteria when screening and investing in entrepreneurial ventures. These criteria are followed by international scalability, profitability, the design of the business model, and the type of existing investors. Using multi-level logistic regression analysis, we then reveal considerable differences in the importance attached to these criteria across investor types. For example, we find that FOs, GEFs, and LBOs heavily emphasize firm profitability. In contrast, BAs and VCs pay less attention to profitability and instead focus on ventures' scalability, as indicated by a higher preference for high revenue growth (VCs) and international scalability (BAs). In addition, our results reveal similarities across investor types. For example, GEFs and LBOs generally consider profitability as more important and also rate ventures' business models as well as current investors as less important.

7.1.2 Chapter 3: A personality perspective on business angel syndication

Chapter 3 analyzes the influence of BAs' personality on their decisions to syndicate investments or invest alone. Our analyses are based on a sample of 3,234 investments by 1,348 BAs which we obtained from Crunchbase. Drawing on research in personality psychology, we use the Big Five personality traits to capture BAs' personality. We utilize a novel method to operationalize BA personality. Specifically, we draw on Receptiviti, a tool to assess language in a computerized way, which we apply to BAs' Twitter profiles in order to infer their psychological traits.

In response to RQ 2, we find that BAs' personality seems to influence their decisions to syndicate. In particular, we find that BAs high in extraversion engage in syndication significantly more often. High values of extraversion reflect a more outgoing and energetic style in social interactions and are associated with a general preference for engagement in social groups. Our findings suggest that this seems to also apply to the context of syndication, which involves frequent interactions with other parties. Additionally, BAs high in conscientiousness, which indicates efficient self-regulation, self-discipline, and achievement orientation, engage significantly less often in syndication. We attribute this to the fact that individuals high in conscientiousness tend to work alone and in a very structured manner. Hence they are better able and more confident to invest alone. We do not find evidence for an association between BAs' decision to syndicate and openness, agreeableness, or neuroticism. A multitude of sensitivity analyses document the robustness of our findings.

7.1.3 Chapter 4: Initial coin offerings (ICOs) to finance new ventures

The emergence of ICOs is one of the latest developments in entrepreneurial finance and Chapter 4 introduces ICOs as a funding mechanism for new ventures. Since the domain of ICOs is largely unexplored, Chapter 4 draws on a manually collected sample of 423 ICOs that were conducted between 2016 and 2018 to explore the determinants of the amount raised in ICOs.

To answer RQ 3, Chapter 4 draws on signaling theory, which suggests that high-quality ventures can attract more funding if they signal their higher quality to potential investors. Since the ICO context is very technology-driven, I argue that signals referring to ventures' technological capabilities will be particularly important. Indeed, I find that a technical white paper as well as a high-quality source code are associated with higher amounts of funding and seem to constitute effective signals in the ICO context. In contrast, patents, a commonly used signal of technological capabilities in prior entrepreneurial finance research, do not influence the amount of funding raised significantly. Since Chapter 4 is an initial assessment of the determinants of ICO success, I include a wide range of control variables to identify further determinants of the amount raised. For example, the results show that higher amounts of funding are further associated with a higher token supply, the implementation of the Ethereum-standard, and a higher Twitter activity. The findings are robust across different model specifications.

7.1.4 Chapter 5: Motives and profiles of ICO investors

Chapter 4 investigates ICOs from a venture perspective. In contrast, Chapter 5 focusses on ICO investors to provide a comprehensive overview of ICOs and the funding dynamics involved. So far, evidence on ICO investors' characteristics and motives is mostly anecdotal. To generate systematic and evidence-based insights on ICO investors, we thus designed and conducted a survey of ICO investors in mid-2018. Overall, 517 ICO investors participated in our survey. In line with the study's exploratory character, the survey included a wide variety of items adapted to the ICO context. The items relate to (1) investment motives when investing in ICOs, (2) sociodemographic information, and (3) ICO investment behavior. To derive our items, we draw on self-determination theory and prior research in the crowdfunding context.

To answer RQ 4, we first perform a principal component factor analysis to identify underlying investment motives. The factor analysis reveals three sets of investment motives: ideological, technological, and financial motives. With regard to the relative importance of these motives, we find that technological motives rated as most important by ICO investors, followed by financial motives and ideological motives. This indicates that ICO investors perceive intrinsic motives as more important than extrinsic motives. Thus, ICOs are not seen as a purely financial investments. Finally, we employ regression analysis to profile investors according to these motives. The results reveal considerable differences between investors high in technological, financial, and ideological motives. For example, a positive association exists between the individual willingness to take risks and high scores in technological motives. Also, reading an ICO's white paper more carefully correlates positively with higher scores in ideological and technological motives.

7.1.5 Chapter 6: Venture capital and the performance of blockchain technology-based firms: evidence from ICOs

The question of how different funding mechanisms interact is of fundamental interest to entrepreneurial finance research. Research shows that VCs invest in emerging high-growth markets, finance new technologies, and play a crucial in the funding of new technology-based firms. Chapter 6 addresses this topic and analyzes the effects of VC participation in ICOs on blockchain technology-based firms' (BTBFs') post-ICO performance.

To answer RQ 5, we collect data on VC participation in a sample of 2,905 ICOs, which we are able to combine with data on ventures' post-ICO performance for a sample of 541 ventures. We employ a restricted control function approach to empirically disentangle selection and treatment effects. The results show that VC participation positively affects post-ICO performance, underlining the overall importance of VC participation in the ICO context. Additionally, we find that this effect cannot be attributed to a selection effect, but is mostly due to a treatment effect. That is, VCs seem to add value to ICO ventures post-investment, which spurs their performance. The result is robust across different measures of post-ICO performance (i.e., growth in market capitalization, liquidity, and profits). In a further analysis, we also show that VC funding positively contributes to ICO success, which we operationalize via the amount raised, ICO duration, and post-ICO exchange listings.

7.2 Implications for theory and practice

Chapter 2's main contribution is twofold. First, the findings contribute to prior research by identifying and comparing the importance of selected investment criteria across different investor types. While prior research acknowledges considerable differences in the decision-making of different investor types (Lerner et al., 2007), our study is the first to document and evaluate them in a comprehensive and systematic way. Second, Chapter 2 enables initial insights on FOs' investment criteria, which have received little attention in prior research but represent an increasingly important asset class. For example, we show that FOs attribute greater importance to the current profitability of portfolio ventures but attribute less importance to their revenue growth. Overall, this finding could be interpreted as reflecting family firms' preferences for wealth perseveration, which is reflected in an investment strategy characterized by lower risk. From a practitioner's perspective, our findings allow PE decision-makers to benchmark their decision-making against peers and across investor types. Also, our systematic assessment of investment criteria allows ventures that seek financing by PE investors to better address the demands of different investor types and to identify the investor type that is in line with their long-term strategy.

While **Chapter 3** introduces personality as a determinant of BAs' decision to syndicate, the chapter's main contribution is methodological. We employ a novel approach to measure personality traits based on digital footprints. Specifically, we apply a language-based method of personality assessment (Receptiviti) to BAs' Twitter accounts, where they willingly and voluntarily publish information about themselves. We show that BAs' personality operationalized via such methods correlates with investment behavior in a way that is consistent with our theoretical predictions. Related methods utilizing individuals' digital footprints are more commonly used in the domains of computer sciences and psychology, where research shows that they are able to reveal very accurate information on a variety of constructs, such as personality, life satisfaction, or sexual orientation (e.g., Kosinski et al., 2013; Youyou et al., 2015).

Chapter 4 introduces ICOs to entrepreneurial finance research. The chapter presents a definition of ICOs, describes the ICO funding process, and assesses the determinants of the amount raised in ICOs. Exploring the determinants of ICO success is a crucial prerequisite for understanding the emergence of ICOs and for evaluating their economic significance. Specifically, Chapter 4 highlights the importance of technological capabilities in the ICO context. Their pronounced importance is a difference between ICOs and other means of entrepreneurial finance, in which technological characteristics are less pronounced. The findings also highlight similarities between ICOs and more traditional funding settings. The results give ventures interested in conducting an ICO a better understanding of how to increase ICO success. For example, the results highlight the importance of communicating technological capabilities when trying to raise funding in the ICO setting. Understanding the factors that drive ICO valuations and the characteristics of high-quality ventures is crucial for policymakers interested in encouraging high-quality ventures or discouraging low-quality ventures.

Chapter 5 takes an investor's perspective on ICOs. Analyzing the motives and profiles of ICO investors is crucial to enable an understanding of the dynamics of ICOs in their entirety. With these findings, our results mainly contribute to the nascent ICO research (e.g., Fisch, 2019; Huang et al., 2019; Masiak et al., 2019; Momtaz, 2019a). Additionally, we draw interesting parallels to prior entrepreneurial finance research, such as crowdfunding, by showing that ICO investors follow similar intrinsic and extrinsic investment motives (e.g., Gerber and Hui, 2013; Allison et al., 2015). Chapter 5 has multiple practical implications. For example, our results document a large heterogeneity among ICO investors, which ICO-conducting ventures can use to more carefully design and communicate their ICO offerings. As such, ventures that want to primarily address technological investors should promote their ICO campaign differently from ventures that intend to primarily attract financial investors. Our findings also show that policymakers should take the heterogeneity among investors into account when trying to regulate the ICO sector. For example, an overly broad regulation that primarily caters to the interests of financial investors while disregarding the interests of technological investors might undermine the innovative potential of the blockchain sector as a whole.

Chapter 6 further contributes to research on ICOs by showing that VC participation in ICOs substantially affects BTBFs' post-ICO performance. We show that VCs' impact is not only visible in terms of BTBF growth, but also in terms of profitability and utilization, underlining the profound benefits of attracting VCs for BTBFs. More specifically, and in line with prior research outside the blockchain sector (e.g., Bertoni et al., 2011; Colombo and Grilli, 2010), we find no evidence for a selection effect but find that the increase in post-ICO performance is mainly driven by a treatment effect. With this result, our findings more generally contribute to entrepreneurial finance research on the performance effects of VC for entrepreneurial ventures (e.g., Baum and Silverman, 2004; Colombo and Grilli, 2005; Rosenbusch et al., 2013). From a practical point of view, our findings underline the importance of attracting VC financing for BTBFs. The findings suggest that BTBFs should try to actively solicit VC participation instead of merely relying on the crowd of (individual) ICO investors. However, ventures should consider the costs of VC participation (e.g., loss of control, discounts) in their decision process. Additionally, our findings inform policymakers that encouraging VC investments in BTBFs might be a useful vehicle to stimulate the growth of the blockchain sector and to ensure its success in the long run.

7.3 Avenues for future research

This thesis opens multiple avenues for future research. Building on the findings of Chapter 2, future research could extend our research on PE investors' decision criteria to other investor types, such as investors in crowdfunding or ICOs. As such, a strong interconnection exists with the finding of Chapter 5. For example, an immediate question is whether and how the investment motives of ICO investors (i.e., ideological, technological, and financial) impact their investment criteria and decision-making. A conjoint analysis, similar to the one conducted in Chapter 2, would enable such insights and would also enable a comparison between the investment criteria of different investor types (e.g., ICOs and crowdfunding). Additionally, Chapter 2 shows that FOs are a neglected yet distinct investor type. Analyzing FOs' investment decisions as well as the performance of these investments provides another promising area for future research. In particular, future research on FOs could draw on and contribute to the well-established literature on family firms.

Chapter 3 shows that BAs' investment behavior correlates with several personality traits, which we operationalized via a method of computerized language assessment based on Twitter. Methods relying on digital footprints (e.g., Twitter, Facebook) have tremendous potential for providing fresh insights to the field of entrepreneurial finance as well as the field of entrepreneurship more generally. For example, such methods are particularly suitable to enable access to data on individuals that are very difficult to reach with traditional data collection techniques, such as surveys (e.g., Obschonka et al., 2017; Obschonka and Fisch, 2018). This not only applies to the field of entrepreneurial finance, but to the field of entrepreneurship in general where such methods could be used to generate novel insights on entrepreneurs, managers, or employees. Additionally, future research could further investigate the importance of individual characteristics in investment decisions. This includes, for example, the influence of further personal characteristics (e.g., overconfidence) of BAs on their decision-making. Also, our findings could be extended to the context of VC decision-making, where investment decisions may also be affected by investment managers' individual characteristics.

A substantial part of this thesis focusses on the emergence of ICOs and the findings of Chapters 4, 5, and 6 open several avenues to advance the nascent research on ICOs. Chapter 4 documents several determinants of ICO success that can serve as the basis for future studies. For example, crucial areas worthy of further investigation concern the role of human capital and social capital as further determinants of ICO success. While such variables have been shown as crucial in prior entrepreneurial finance research (e.g., Ahlers et al., 2015; Allison et al., 2017; Baum and Silverman, 2004), they are more difficult to grasp in the ICO context. The findings of Chapter 4 also suggest that technological capital could play a more important role in ICOs, potentially making human and social capital less important. As such, future research could assess and compare further variables and their relation with ICO success.

Chapter 5 reveals that ICO investors are motivated by a set of intrinsic and extrinsic motives. Generally, ICO investors perceive intrinsic motives as more important. Our insights rely on data that was collected in 2018. From 2018 to 2019, the market for cryptocurrencies and ICOs has seen a strong decrease in valuations. As such, it would be interesting to assess whether investment motives and their perceived importance have changed or whether they are relatively stable. Furthermore, combining data on ICO investors and data on the ICOs they invest in could advance the understanding of how investment motives and venture characteristics interact. Such information could be used by ventures trying to appeal to a specific type of ICO investors when designing their ICO offering.

Finally, Chapter 6 introduces VCs as an important and value-providing intermediary in the ICO context. An avenue to advance these findings lies in a more fine-grained investigation of VC perception. For example, prior research shows that VC investments by highly repeated investors are more beneficial to venture performance (e.g., Hsu, 2004). Similarly, backing by a VC with a high reputation might influence BTBFs' post-ICO differently than backing by unknown VCs. Other differences might emerge with regard to the VC investor's knowledge in the blockchain sector. Highly specialized VC might have a more profound effect on venture performance than less specialized VCs. A final area of interest concerns VCs' exit strategies. While Chapter 6 documents a positive association between VC participation and post-ICO performance, it is unclear whether and how VCs can benefit from these performance increases. The ICO context is particularly suitable for studying exit strategies since VCs can easily exit ventures by selling their tokens in the secondary market. This also raises the question of how a VC's exit affects the venture.

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