Essays in Entrepreneurial Finance

by

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To my family

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CHAPTER 1

Synopsis

Abstract

This chapter provides a brief introduction to the area of entrepreneurship and entrepreneurial finance research, specific to the topics covered in the following chapters. First, it outlines the motivation behind the dissertation. In a second step, it gives an overview of the three interdependent research projects comprised in this dissertation and summarizes the empirical key results. The final section concludes.

1.1 Motivation

Entrepreneurship is germane to the creation, development, and growth of new technologies, industries, and markets of knowledge-based economies (Megginson (2004), Block et al. (2016)). For example, according to the Kauffman Index of Entrepreneurship, businesses that were less than three years old created almost all new jobs in the US over the past two decades (Looze and Goff (2022)). As such, the field of entrepreneurship is an integral component of economic growth and therefore of considerable interest to practitioners, researchers, and policy-makers alike. Considering the importance of entrepreneurial ventures to the overall economic system, the three articles comprised in this dissertation address novel questions about the internal and external characteristics that drive entrepreneurial decision making and success.

Despite the well-known benefits of a thriving entrepreneurship ecosystem, the financing for young and highly innovative firms is the most critical hurdle that founders must overcome (Carpenter and Petersen (2002)). In their early stages, new ventures have no operating history and are in consequence constrained by internal resources such as private savings or operational cash flows (Sahlman (1990), Amit et al. (1998)). Further, being subject to the liability of newness (Stinchcombe (1965), Hannan and Freeman (1984), Baum (1996)) and the liability of smallness (Stinchcombe (1965), Hannan and Freeman (1984), Carroll and Hannan (2000)), these firms face difficulties in obtaining capital from traditional sources of finance such as banks or other credit institutions (Amit et al. (1998), Gompers and Lerner (2001), Tykvová (2007)).

For these reasons, entrepreneurial ventures need to obtain external capital to finance the early founding stages (e.g., development of initial products and services, recruitment and hiring of first employees or execution of R&D and further market research), as well as later growth stages (e.g., adaptation of products and services, international expansion, or increased marketing activities) of the firm. While the financing of entrepreneurial ventures is characterized by substantial information asymmetries and agency problems between the entrepreneur and the financiers, venture capital (VC) has been advocated as an important source of financing for these high-risk, potentially high-reward ventures (Gompers and Lerner (2001)).

Jeng and Wells (2000) generally classify VC as one type of private equity investing. In contrast to regular, passive retail investors, private equity investors are institutions or wealthy individuals. By taking an equity stake of both publicly quoted and privately held companies, they regularly obtain additional control and information rights and are hence more actively involved in building and managing their portfolio companies. It is important to note, that the private equity subfield of VC is defined differently in the US and Europe. Outside the US, VC frequently includes other main types of private equity investing, namely management and leveraged buyouts. In line with Jeng and Wells (2000), this dissertation defines VC as private or institutional investments in entrepreneurial, i.e., seed- or growth-stage, ventures via equity or equity-like instruments. Due to its size and importance for the financing of new ventures, VC constitutes the central and most prominent part of the research field of entrepreneurial finance (Gompers and Lerner (2001), Puri and Zarutskie (2012), Bellavitis et al. (2017), among others).

To date, much of the research on entrepreneurship and entrepreneurial finance has focused on the impact of venture human capital, specifically team and founder characteristics, and the associated implications on firm and investment success. Numerous empirical studies have explored venture team demographic characteristics (Beckman et al. (2007), Eddleston et al. (2016)), team diversity (Chowdhury (2005), Brandy and Hillmann (2018)) and task-relevant characteristics of founders and team members such as education or experience (Cohen and Dean (2005), Beckman et al. (2007), Becker-Blease and Sohl (2015)). In addition, the literature has utilized social network theory to study the impact of established firms' social capital, namely their CEOs (Hwang and Kim (2009), Fracassi and Tate (2012)) and boards of directors (Geletkanycz and Hambrick (1997), Larcker et al. (2013), Fracassi (2017)) on firm value and decision making. Furthermore, scholars have documented a positive link between investor centrality and investment performance (Hochberg et al. (2007), Ozsoylev et al. (2013), Werth and Boeert (2013), Bajo et al. (2020)). While the existing literature on entrepreneurial networks mostly studies egocentric networks of the founders and how these are associated with firm success (Shane and Cable (2002), Mollick (2014), Vismara (2018)), there remains uncertainty whether the social ties created by entrepreneurial team members are similarly related to signals of quality and information advantages that are relevant to success.

The first study of this dissertation, entitled "Team networks and venture success: Evidence from token-financed startups", addresses this gap in the literature and investigates the impact of team networks on venture performance in the post-funding stage. We examine the venture success-team centrality relationship by using the example of the token offering market. Token offerings provide an ideal research setting to extend the social network literature in entrepreneurial finance. In particular, we are able to investigate the performance implications of team networks at different stages of the venture life cycle and cover long-term indicators of entrepreneurial success such as post-funding liquidity and market value. Enabled by the internet, token offerings have emerged as an innovative funding mechanism that allows entrepreneurial ventures to publicly solicit and raise capital from a large number of often private individuals without the involvement of intermediaries (Momtaz (2019)). Having spread across emerging and developed countries, the phenomenon is vividly discussed in theory and practice (Vismara (2018), Fisch (2019), Momtaz (2019), Vanacker et al. (2019), Cumming et al. (2022), Florysiak and Schandlbauer (2022), among others).

Another aspect entrepreneurial finance research has focused on is the role VC investors (VCs) play in contributing to their portfolio firms' decision making and success. Overall, financial economists agree on the positive relationship between the presence of VC and entrepreneurial success (Davila et al. (2003), Colombo and Grilli (2010), Sampsa and Sorenson (2011), Dutta and Folta (2016), among others). Based on VCs' active involvement in the creation and management of their portfolio companies, the extant literature has highlighted two mechanisms through which VCs positively influence seed- and growth-stage ventures. First, VCs' superior screening and monitoring capabilities allow them to "scout" entrepreneurial projects and talent with a higher probability of success. Second, and of higher importance to the venture itself, VCs "coach" their portfolio firms. VCs actively augment startups' resources and capabilities by advising them in fields, where young ventures typically lack internal capabilities, such as strategic planning, accounting, and human resource management. Previous literature provides general support for these theories (Amit et al. (1998), Hellmann and Puri (2002), Bottazzi et al. (2008), Colombo and Grilli (2010)). In the context of these theories, a lengthy literature has discussed the tools and control mechanisms that VCs use to overcome the problems of information asymmetry (Sahlman (1990), Lerner (1994), Gompers (1995)).

Building on the extensive growth and increasing internationalization of the VC market (Schertler and Tykvová (2011), Chemmanur et al. (2016)), international VC investment has been subject of considerable study in the entrepreneurial finance literature. Prior work in the field of international VC primarily relates to the presence of cross-border investors in general and geographical and cultural distances towards their investees, i.e., the entrepreneur-VC dyad (Cumming et al. (2009), Devigne et al. (2013), Humphery-Jenner and Suchard (2013), Li et al. (2014) among others). The evidence that ownership heterogeneity affects public equity outcomes (Ng et al. (2015), Huang and Petkevich (2016)) suggests that the extent of heterogeneity among startup investors matters for success. Although, for example, the majority of US startups is backed by multiple VCs that share transaction costs and risks related to entrepreneurial financing via syndicated investments, past research has not considered the specific implications of heterogeneity among investors in the VC market.

The second study of this dissertation, entitled "Venture capital investor heterogeneity and funding success", examines how heterogeneous VC ownership can impact the success of entrepreneurial ventures. Specifically, we investigate if financing from investors with diverse cultural backgrounds affects a startup's ability to attract new funding and grow. To gain insights on the effects of cultural differences in entrepreneurial financing, we draw on the cultural theories of Hofstede. The results of this study provide valuable insights into the VC-related mechanisms that affect entrepreneurial success. Furthermore, our research has important implications for entrepreneurs, who seek smart money and hands-on investors (Gompers and Lerner (2004)), since selecting the right VC partners can improve entrepreneurs' chances of success.

While the entrepreneurial finance literature has paid disproportionately more attention to analysing the internal and external drivers of economic performance, the traditional concept of shareholder value has been more and more replaced by an integrated view of corporate value creation that incorporates social and environmental externalities. The literature on public equity investment provides substantial evidence of the active influence of institutional investors on corporate environmental performance (Chen (2019), Dyck et al. (2019), Krueger et al. (2020)), but little is known about the relationship between sustainability-oriented ownership and startups' environmental performance. As existing entrepreneurial finance literature suggests a positive relationship between environmental and economic performance (Friede et al. (2015), Bauckloh et al. (2021), Mansouri and Momtaz (2022)), a better understanding of the factors that contribute to the environmental performance of firms is a critical aspect of entrepreneurship studies. Thus, the third study of this dissertation, entitled "On the impact of sustainable venture capital", aims to fill this gap by providing new insights into the unexplored relationship between VC investments and the environmental performance of early-stage firms. Building on existing literature that studies the role of institutional investors in promoting sustainable development (Petkova et al. (2014), Barber et al. (2021), Gillan et al. (2021), among others), our study is the first to provide empirical evidence on the capabilities of VCs to affect the environmental outcomes of their investees in the early stages of the firm life cycle.

The remainder of this introductory chapter is structured as follows. Section 1.2 provides a brief summary of the three interdependent research projects cumulated in this dissertation. Finally, Section 1.3 summarizes and concludes.

1.2 Overview of research projects

This dissertation consists of three empirical studies that focus on the implications of venture and investor characteristics in supporting and building innovative and sustainable businesses. The three projects focus on team networks (see Chapter 2), VC investor heterogeneity (see Chapter 3), and sustainable VCs (see Chapter 4). Above all, the compendium of the articles and empirical analyses that constitute this dissertation aim to give answers to the questions which factors drive entrepreneurial decision making processes and financial success. They identify and apply state-of-the-art methods, such as social network and linguistic analysis, in combination with more established techniques to address endogeneity concerns, which is of particular importance in all subfields of entrepreneurship research. The following paragraphs provide some background information on each paper and summarize the empirical methods and key contributions of the studies.

Chapter 2. Team networks and venture success: Evidence from token-financed startups. The first study, co-authored with Wolfgang Drobetz and Henning Schröder, focuses on the social capital, i.e., network centrality, of entrepreneurial ventures. Following the positive relationship between social network ties and firm performance that has been documented by previous research (Hochberg et al.

(2007), Fracassi and Tate (2012), Fracassi (2017), among others), we assess how team and advisory committee networks determine post-funding success of young ventures in the blockchain industry. Existing literature on the performance implications of networks in entrepreneurial finance is relatively nascent and primarily studies the relations between founder networks and funding success (Mollick (2014), Vismara (2018)). To the best of our knowledge, prior work has not yet approached the question how the connectedness of early-stage firms translates into post-funding, i.e., long-term, success. Specifically, we argue that higher liquidity and venture value on the secondary market are related to quality signals and information benefits provided by more central actors.

Since the mid-2010s, the academic interest in the field of token offerings (also referred to as initial coin offerings or token sales) has increased considerably. The popularity of this new research field is partially driven by the high amounts of provided capital (Blaseg (2018), Momtaz (2020)). Over and above, token offerings exhibit structural similarities to conventional IPOs (Momtaz (2019)). As these tokens get frequently listed on the secondary market, i.e., crypto exchanges, this enables researchers to conduct quantitative analysis on funding performance and aftermarket success. Therefore, we consider the token offering market as the ideal setting to examine the economic outcomes of startups in the post-funding stage.

First, we build a sample of 129 ventures trading on token exchanges in the period of 2017 – 2019. We follow previous research (Momtaz (2020), Florysiak and Schandlbauer (2022), Lyandres et al. (2022), among others) and measure post-funding success using indicators drawn from IPO research such as trading volumes and market-to-book ratios. Furthermore, we borrow from social network theory (Freeman (1978)) to measure venture centrality to capture the quality of relationships and information flows in our research setting on a monthly basis. In particular, we resort to four different centrality measures commonly applied in the literature (Freeman (1978), Bonacich (1987)). As these individual metrics capture different aspects of an object's position, we follow Larcker et al. (2013) and calculate a composite centrality measure for two groups: team members and advisors. While team members are actively working on the development and implementation of potential future products funded by token offering investors, the support of external advisors usually ends with the token offering. By distinguishing the two groups, we are able to examine whether the network of the advisory committee remains relevant once the venture is initially funded.

In a next step, we examine whether centrality provides a quality signal and information benefits resulting in long-term firm success using two different indicators of aftermarket performance, i.e., the monthly token trading volume and the average monthly market-to-book ratio of each venture. Our analyses show that centrally positioned teams are positively related to both, liquidity and value. While our results also hold after controlling for potential endogeneity concerns, additional robustness tests show that advisor centrality is mainly unrelated to ventures' post-funding success. Furthermore, we show that team centrality has a particularly strong influence on post-funding venture success in the absence of tangible information, i.e., informative white paper documents.

Overall, the empirical results of this study contribute to the understanding of a potential certification effect and a connection premium provided by social network ties. We highlight the importance of social capital in the context of entrepreneurial ventures and suggest that well-connected teams are an important determinant of long-term venture success.

Chapter 3. Venture capital investor heterogeneity and funding success. The second study examines whether investor heterogeneity drives entrepreneurial funding. Over the past few decades, advancements in technology and globalization have created more and more possibilities for VC firms to seek out investment opportunities outside their home country. However, existing studies document that institutional, national and cultural distance between the investor and entrepreneur raises barriers to information sharing, reduces trust, increases transaction costs and, ultimately, the potential for conflict (Dai et al. (2012), Li et al. (2014), Nahata et al. (2014), Dai and Nahata (2016)). We argue that even though VCs can jointly invest in one firm through syndication, a group of investors may not have entirely common goals as they do not represent a homogeneous population. Thus, we hypothesize that local and especially cultural disparity among VCs affects the future success of yet early-stage portfolio firms.

To test our hypothesis, we build a comprehensive sample of young ventures in the US that sought VC funding in the period of 2010 – 2022. Drawing on recent work in the entrepreneurship literature (Butticè et al. (2022), Guzman and Li (2023), among others), we use Crunchbase as our primary database. The platform provides extensive data on VC investments and allows us to trace the local and cultural origin of involved VCs. We aim to capture the extent to which startups are impacted by a diverse investor structure, and therefore construct different heterogeneity measures. These include multidimensional indices of investors' cultural backgrounds using Hofstede's cultural dimensions, an index measuring the probability that two randomly selected investors originate from the same country using Blau (1977)'s calculation approach and a geographical distance measure.

After controlling for various firm and investor characteristics and addressing endogeneity concerns using a two-stage Heckman correction model and an adjusted instrumental variables approach, we find that the probability of receiving future VC funding is negatively and significantly related to cultural heterogeneity among VCs. Additionally, the results are robust to our battery of alternative investor heterogeneity measures. We also examine the funding size to shed light on the economic relevance of heterogeneous VCs and document that an increase in the heterogeneity of investors is negatively and significantly related to the amount raised in future entrepreneurial funding rounds.

Our study is the first to explore the role of investor heterogeneity in the context of early-stage ventures. Overall, the findings of this study contribute to the understanding of how ventures financed by investors with diverse backgrounds influence entrepreneurial success. Given the importance of VC as a stimulus for economic growth, it is crucial for entrepreneurs and investors to have a thorough understanding on the effects of heterogeneous ownership structures in entrepreneurial finance.

Chapter 4. On the impact of sustainable venture capital. While the first two studies focus on the drivers of startups' financial performance, the third study, which is co-authored with Marwin Mönkemeyer and Henning Schröder, analyses the environmental performance of early-stage firms and whether this is driven by sustainability-oriented VCs. Given the documented impact of sustainability-oriented investors in public equity (Dyck et al. (2019), Chen (2019), Krueger et al. (2020)), we examine the influence of VCs that have signed the United Nations Principles for Responsible Investment (PRI) on their portfolio companies' environmental performance. Specifically, we hypothesize that a higher share of PRI signatories, i.e., committed sustainable investors that integrate environmental, social and corporate governance (ESG) criteria in their investment strategy, shapes entrepreneurs' decision making and efforts to build more sustainable businesses.

In an initial step, we quantify startups' environmental performance. As commercial measures of ESG performance are rarely available for firms in the funding stage, existing research faces difficulties to provide a coherent yardstick of startups' environmental performance. We follow Cumming et al. (2022) and adapt an innovative machine learning approach introduced by Mansouri and Momtaz (2022) to extract a measure of environmental performance at the firm-year level applying textual analysis on our sample firms' Twitter feeds.

The empirical results reveal that PRI-compliant VCs have a statistically significant and economically meaningful impact on entrepreneurial environmental performance. Moreover, the results of our baseline specification are robust to controls for sources of observed and unobserved heterogeneity across firms, industries, and time. Further regression results show that early adopters of the PRI, i.e., strongly committed VCs, primarily drive portfolio firms' environmental performance. This is in line with the conjecture that late adopters of the PRI are less active in implementing the initiative's principles (Bauckloh et al. (2021)). To explain the variation of environmental performance across firms, we interact PRI ownership with different dummy variables indicating whether (i) the startup already performs well regarding environmental aspects and (ii) whether it is headquartered in a country with a strong focus on environmental actions. We find that the effect of sustainable VCs is greater in firms with relatively low environmental performance levels, i.e., those firms with a high upside in environmental performance. Furthermore, the empirical results indicate that PRI investors play a significantly stronger role in improving startups' environmental performance in environmentally sensitive countries. In regard to potential endogeneity issues resulting from measurement error in our key explanatory variable, we alleviate these concerns by using alternative proxies for sustainable VCs in further robustness tests.

The second part of the study analyses the presence of PRI investors and whether it is associated with improved environmental performance in the post VC-financing phase, i.e., the post-IPO stage. In later stages of the firm life cycle, we are able to capture our sample firms' environmental performance with a commercial measure widely used in the literature (Luo et al. (2015), Chatterji et al. (2016), Ghoul et al. (2017), among others), the Thomson Reuters (TR) environmental pillar score. In line with our baseline specification, we address the possible existence of a selection effect by applying a two-stage Heckman correction and an adjusted instrumental variable model. Our results confirm that the early impact of sustainable VCs manifests in long-run effects that last up to several years after the portfolio firms' IPO.

With this study, we provide first-time evidence on the role of sustainable VCs in promoting environmental firm characteristics and preferences at different stages of the firm life cycle. Overall, the findings of this study contribute to the entrepreneurial finance literature that has thus far neglected environmental components in VC and add new insights on the ownership-related factors that foster the building of environmentally sustainable businesses.

1.3 Conclusions

The three studies comprising this dissertation examine recent phenomena in the field of entrepreneurial finance. The first paper analyses the importance of well-connected teams in sending positive signals to the market and overcoming information frictions, which ultimately translates into long-term financial success. The second study aims to elucidate investor-related determinants of VC funding success. In particular, the study tests whether heterogeneity among VCs influences the probability and size of future entrepreneurial funding. The empirical results provide evidence that new venture funding is strongly affected by the degree of cultural and geographical heterogeneity among VCs. The third study examines how VCs' commitment to sustainability affects the environmental performance of their portfolio companies. By using a novel machine-learning approach to quantify the environmental performance of yet unlisted firms, the results suggest that investors' pledge to initiatives such as the PRI strongly affects short- and long-term environmental performance of VC-financed firms.

This dissertation adds to the entrepreneurship and entrepreneurial finance literature by providing further evidence on how investors and entrepreneurial ventures overcome information asymmetry and agency issues in the risk capital market for early-stage firm investments. It also suggests promising avenues for future research. While the first two papers analyse both, new and traditional, early-stage financing mechanisms and the associated drivers of financial performance, the third study approaches the question of whether investor characteristics also determine environmental performance. The results indicate that VCs' traditional focus on the business and the financial traction caused by the return expectations of their limited partners, is experiencing a shift towards sustainability aspects. This creates ample room for future research and more explicit insights into how institutional investors can effectively contribute to a sustainable and financially sound economy.

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CHAPTER 2

Team Networks and Venture Success: Evidence from Token-Financed Startups

WITH

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Abstract

Evidence shows that social network structures drive important economic outcomes. Building on social network theory, this study is the first to analyse the impact of team networks on venture success. Using information about team affiliations for a sample of token-financed startups, we model networks based on team interlocks across firms. Ventures with well-connected teams exhibit higher market valuations and higher token market liquidity. These effects seem to be driven by network-induced information and communication advantages. Specifically, we show that networks matter most when publicly available information is limited. The findings remain robust after controlling for non-team networks and endogeneity.

2.1 Introduction

This paper examines how social networks impact the success of ventures that have undertaken token offerings, i.e., issued blockchain-based crypto tokens to raise external growth capital. Specifically, we analyse how ventures' success is affected by their positions in the token market's social network. Defining network ties based on team interlocks with other ventures in the token market, we follow social network theory and construct different network centrality measures to assess how team networks determine post-funding success in terms of token liquidity and market valuation. Our results indicate that more central teams obtain information and communication advantages through their networks and utilize them to build a sustainable and successful business after the initial funding phase. Additional robustness tests reveal that team networks seem to be more important than the non-operational (external) advisor networks of our sample ventures. These findings provide empirical evidence that effective team networks improve entrepreneurial decision making at the post-funding stage.

Our study relates to various strands of literature. Recently, there has been growing interest in understanding how the context in which firms are socially embedded impacts their behavior and performance. Empirical evidence shows that social network structures drive important economic outcomes (see Bianchi et al. (2023) for a literature survey). According to Borgatti and Halgin (2011), a social network is defined as a set of actors (nodes) in a system, along with a set of links (edges), that can represent interactions (e.g., who receives information from whom), similarities (e.g., common educational background), or comembership in groups (e.g., clubs or, in the framework of our analysis, the entirety of ventures that issue tokens). Previous studies in sociology, corporate finance, and management literature offer two competing arguments on the implications of being "well-connected".[1]

The majority of studies provide evidence that networks have positive outcomes, e.g., because they build up social capital. For example, in the context of venture capital investment performance (Hochberg et al. (2007)), institutional investors (Cohen et al. (2008), Bajo et al. (2020)), analyst recommendations (Cohen et al. (2010)), and corporate investment (Fracassi (2017)) network ties appear to provide a factor for success by facilitating information flows. However, networks can also have a "dark" side, e.g., because they create social homogeneity that in some cases generates negative outcomes. Weaker corporate governance, seemingly also caused by network ties, has been found to distort CEO retention decisions (Nguyen (2012)), corporate investment (Fracassi and Tate (2012)), and director selection (Kuhnen (2009)).

So far, scholars have predominantly investigated the influence of managers' or directors' personal networks on the performance of established, i.e., listed, firms. For example, Larcker et al. (2013) provide evidence that well-connected boards are characterized by superior risk-adjusted stock returns and higher future growth in return-on-assets. Fracassi (2017) studies executive social networks and finds that firms with centrally located managers are associated with higher performance and firm value. In contrast, evidence on social network attributes that influence startup and entrepreneurial venture performance is still scant.[2] Hochberg et al. (2007) are among the few who examine the relation between entrepreneurial networks and performance. They document that better networked venture capitalists experience significantly better fund performance.

The lack of social network studies in the context of young ventures is in large part due to extensive data constraints. Post-funding financial performance data as well as detailed information about team affiliations are rarely available for "regular" startups. However, both is essential to empirically analyse the impact of social networks on venture success metrics which go beyond pure funding and exit performance. As such, the market of token-financed ventures constitutes an ideal framework to further analyse the impact of team networks on venture success across time as team information is publicly available and continuous data on ventures' market valuations and token liquidity (two key financial success metrics from the corporate finance perspective) are readily observable via crypto exchanges.

Since blockchain technology was introduced in 2008, the token offering market has attracted heavy interest from academic research. A token offering is a type of public offering in which a blockchain technology venture issues tokens to investors. These tokens provide investors the access to use services of the venture (utility tokens) or acquire ownership of the venture itself (equity tokens). The year of breakthrough was the year 2017, when over 1,000 ventures sought funding via a token offering. Moreover, the market capitalization in these so-called alt-coins (the term comes from "alternative coins" as opposed to the dominant coin, "Bitcoin") increased by about $370 billion, exceeding the entire European venture capital industry (Amsden and Schweizer (2018), Blaseg (2018), Mansouri and Momtaz (2022)).

Empirical literature on the development, magnitude, and economic capabilities of the token offering market is expanding rapidly (see Momtaz (2020) for an excellent overview). Previous studies in the context of venture teams utilizing digital tokens as a growth capital source show that human capital characteristics such as team size (Lyandres et al. (2022)), CEOs' age and education (Momtaz (2021a)) or expert ratings (Momtaz (2020), Florysiak and Schandlbauer (2022)) are related to venture success. While most of the literature focuses on the characteristics of the token offering market and individual team traits, Giudici et al. (2020) were among the first to provide evidence that the ventures' networks also matter for their success. Specifically, they document that ventures' advisor networks drive success during the initial token-offering phase. However, the authors neglect the impact of social networks at the ventures' operational level, i.e., how team networks affect venture success. Moreover, they limit their analysis to the very early funding stage instead of focusing on long-term financial success.

We fill this research gap and contribute to the growing strand of literature that studies success factors of young ventures opting for token-based fundraising (Adhami et al. (2018), Fisch (2019), Momtaz (2021b), Bellavitis et al. (2022), Mansouri and Momtaz (2022), among others). Thereby, our empirical analysis is based on a newly combined data set that comprises team affiliations as well as market performance metrics of all token-financed ventures listed on the major crypto platform Coinmarketcap. This empirical framework is not only suitable from a data perspective but has also some crucial advantages from the economic perspective. First, unlike conventional startup financing methods such as venture capital transactions, token offerings happen largely on the internet and provide access to institutional and retail investors alike. Based on the information about team members that is typically disclosed during the fundraising process, the characteristics of and ties between venture teams are readily observable. Second, lacking legal investor protection and information disclosure laws, the market features high levels of information asymmetry between investors and entrepreneurs (Adhami et al. (2018), Block et al. (2021), Momtaz (2021a), Florysiak and Schandlbauer (2022)). As only few institutional investors (able to conduct in-depth due diligence) are active in the market, adverse selection problems generally arise with these ventures that possess highly innovative and visionary business models. Therefore, intangible investment-relevant information such as a team members' network and the ensuing information advantages gain importance for investors' decision in the absence of tangible reference points in an uncertainty-plagued transaction context (Fisch (2019), Howell et al. (2019), Momtaz (2021a)). Third, the quality of relational ties and network positions determines the level of information and experience sharing across connected ventures, which in turn improves ventures' action coordination and efficacy (Horton et al. (2012), Chuluun et al. (2017)). Individuals who repeatedly interact with each other, experience elevated levels of mutual trust and trustworthiness (Coleman (1988), Glaeser et al. (2000)). Consequently, network centrality creates social liabilities among and between venture teams, which contributes to reducing information asymmetry (Fogel et al. (2018)). Exploiting relational ties and network positions improves the access of ventures to information that is necessary to create intellectual capital and organizational advantages (Nahapiet and Ghoshal (1998)).

The main construct of interest in our study is the "well-connectedness" or, in graph theory terms, centrality of teams established by their formal or professional ties. Our approach is structuralist (Bianchi et al. (2023)) in that we study the entire patterns of ties in a network structure, i.e., we capture the relations among all actors by incorporating both direct and indirect relations. Following Larcker et al. (2013), we conceptualize shared team members between two ventures as channels of information or resource exchange and study a venture's degree of connectedness using standard tools of analysis developed by social network theory. The position in the whole network of direct and indirect relations is important for information diffusion. Since highly central teams are closer to the network's aggregate flow of information and thus provide an intangible quality signal to the market, our overarching hypothesis is that team networks are positively related to venture success.

Our results underline that well-connected teams seem to have information advantages, attenuate information frictions between the venture and external investors, provide positive signals to the market, and eventually improve venture performance in terms of trading volume and market-to-book ratio on the secondary market. Furthermore, our paper documents that the level of tangible information shared by the focal and connected ventures moderate the centrality-venture success relations. Consistent with Giudici et al. (2020) and Momtaz (2021a), we provide credence to an explanation based on dissemination of information and signalling mechanisms through networks by showing that the centrality-venture success relation is strongest in situations when tangible information is missing. In particular, our results are most pronounced if the focal venture fails to distribute informative white paper documents. When such high-quality signals are not available, investors' trading activity and post-funding performance increase sharply with the presence of teams that are centrally positioned in the entire venture network. In this situation, when public information relevant for a venture's success is absent, team members' access to network information is particularly valuable, and well-connected team members themselves serve as a signal of venture quality. In other words, there seems to be a substitution effect between informal information flows within networks and more formal information contained in published white paper documents.

Finally, we document that the external advisor networks have no uniform effect on venture aftermarket success. Contrary to the relevance of advisor networks for the initial funding success (Giudici et al. (2020)), our findings indicate that advisor networks lose relevance as soon as the venture has been initially funded. This is consistent with the notion that team members have incentives to remain committed to further build up the venture and create long-term value, while advisors' support usually ends with the token offering. All key results of our study remain robust after accounting for potential endogeneity concerns in the estimation process.

2.2 Related literature

2.2.1 Networks and firm success

There exists a large body of literature that examines the influence of social networks on firm success from different perspectives. Previous studies in sociology, finance, and management literature offer two competing arguments on the performance implications of social networks.[3] On the one hand, scholars document weaker corporate governance seemingly caused by network ties, thus supporting the hypothesis that centrality negatively affects firm success. For example, Nguyen (2012) documents a negative network impact on corporate governance; in particular, social ties between the board of directors and the firm's CEO reduce the likelihood of CEO dismissal for poor performance. Accordingly, Kuhnen (2009) finds that connections between fund directors and advisory firms facilitate preferential director selection, while Fracassi and Tate (2012) show that firms with more CEO-director ties engage in more value-destroying acquisitions, indicating that CEOs' network ties weaken the intensity of board monitoring.

On the other hand, several studies provide evidence that centrally located actors have access to superior and more timely information than more peripheral actors. Hochberg et al. (2007) examine the effect of syndicated venture capital investments and find that better-networked venture capitalists experience significantly better fund performance, i.e., realized exits through an IPO or acquisition by another company. Similarly, several studies document the existence of a *connection premium* for stock portfolios held by investors connected through their educational or professional network (Cohen et al. (2008), Ozsoylev et al. (2013), Rossi et al. (2018), Maggio et al. (2019)) as well as stock recommendations from analysts linked to the company via school-ties (Cohen et al. (2010)). In addition to this connection premium, Bajo et al. (2020) show evidence of a *certification benefit* of network relationships. They document that block-holdings from more central, active institutional investors enhance firm value more than those held by peripheral investors. However, the empirical work is not limited to the link between investor connections and investment performance. Related to our work, there exists a strand of literature which focuses on firms' executive social networks (top management and boards of directors). Evidence reveals that stronger networks at the executive level allow firms to make better policy decisions which eventually translate into better operating performance and firm value (Geletkanycz and Hambrick (1997), Larcker et al. (2013), Fracassi (2017)).

Despite the broad empirical evidence regarding the performance implications of network connections in the case of established firms, little is known about the value of social networks outside the universe of mature and publicly listed firms. So far, only few studies consider venture network structures relevant in the context of conventional startup financing such as angel investments and crowdfunding. Related to the literature on institutional investor networks, Werth and Boeert (2013) find that startups of better-connected angel investors are more likely to receive subsequent funding by venture capitalists and business angels, and further exhibit a higher probability for successful exits. In general, the existing literature on entrepreneurial networks mostly studies the impact of egocentric founder networks across different social (business) network platforms like Twitter or LinkedIn. For example, Mollick (2014) shows that founder centrality is positively associated with fundraising success of projects resorting to reward-based crowdfunding.[4] Similarly, Vismara (2018) finds that the social network of entrepreneurs increases the probability of entrepreneurial success by increasing the likelihood of raising funds in equity-crowdfunding campaigns. Despite of these exceptions, the literature on the firm performance implications of networks in entrepreneurial finance is relatively nascent and requires further investigation.

2.2.2 Token-based venture financing

This study aims to draw evidence on the team network-venture success relation from analysing the case of token-financed startups. Token offerings, also referred to as initial coin offerings or token sales, are a new financing method based on smart contracts using blockchain technology to issue digital tokens or coins (Adhami et al. (2018), Momtaz (2019)). In exchange for wired fiat money or cryptocurrencies, investors receive tokens from the fundraising venture. After the initial funding period tokens are typically listed on crypto exchanges which provide a liquid secondary market, enabling investors to trade tokens with one another (Adhami et al. (2018), Fisch (2019), Momtaz (2020), Bellavitis et al. (2022), Mansouri and Momtaz (2022)). Token offerings have become a funding alternative especially for early-stage projects as traditional intermediaries, such as venture capitalists, and the related transaction costs can be bypassed.

The idea of token offerings was first applied in 2013 and had its breakthrough in 2017, when about 1,000 token offerings sought funding and exceeded the entire European venture capital industry (Blaseg (2018), Momtaz (2021a)). Since the ventures' business is in its earliest stage and advertised products and services are predominantly in the development phase, token offerings are characterized by strong information asymmetry and opacity (Adhami et al. (2018), Block et al. (2021), Momtaz (2021a)). In accordance with the novelty of the financing mechanism, academic research on token offerings is still in its early stages. Token offerings are often compared to conventional crowdfunding campaigns in that early investment opportunities are provided to the public in the primary market (Arnold et al. (2019), Momtaz (2019)).[5] Initial work mostly studies determinants of funding success and amount (Adhami et al. (2018), Amsden and Schweizer (2018), Fisch (2019), Giudici et al. (2020)).

An evolving strand of literature examines financial market outcome, i.e., market adoption measured by liquidity and aftermarket value as well as determinants of the operational progress in the post-funding phase of the venture (Howell et al. (2019), Benedetti and Kostovetsky (2021)). Since token offerings grant early investment opportunities to the public, but also provide secondary market liquidity, studies on post-funding performance of token offerings heavily draw from IPO research using aftermarket performance measures such as buy-and-hold and first-day returns (Momtaz (2020), Momtaz (2021b), Lyandres et al. (2022)).[6]

Overall, token offerings are an ideal setting to provide further insights on the performance implications of entrepreneurial networks for at least two reasons. First, network literature in the context of entrepreneurial ventures is prone to constraints in obtaining reliable and publicly available data for quantitative analysis on funding performance and aftermarket success (Vismara (2018)). Similar to IPOs of corporate securities where aftermarket performance, i.e., price level variation of the newly issued stock, is transparently observable, tokens trading on crypto exchanges such as *Coinmarketcap* enable us to observe ventures' financial performance at daily frequency. While tokens are usually listed a few days post-offering (Benedetti and Kostovetsky (2021)), financial outcomes of alternative startup financing mechanisms such as crowdfunding or venture capital only become available when the startup is acquired or goes public, which might be years after the initial funding round (Colombo et al. (2022)). Even more generally, the post-funding phase of young ventures is probably "the least explored" (Vanacker et al. (2019, p. 237)) topic in crowdfunding research as only a few studies provide insights on the post-funding performance of token offering and crowdfunding projects (for a review see Mansouri and Momtaz (2022)).

Second, as no audited offering prospectus or third-party screening is required to conduct a token offering, information asymmetry and opaqueness in the market are particularly severe, and the risk of moral hazard is high. However, it is standard practice that ventures targeting investors via token offerings publish extensive white papers, resembling a prospectus filed for offering of stocks, bonds, and mutual funds, and promote their project on platforms such as *ICObench* which provide one-stop access to relevant information for token investors. In doing so, important information on the venture's human and social capital, including team composition, team member characteristics and project track record becomes publicly available. Team quality and social capital expressed by the venture's connectedness are one of the few signals investors can observe and may therefore reduce agency problems. At the same time, the available detail on team composition enables us to conduct social network analysis and investigate whether intra-firm network connections matter for venture success at different stages.

2.3 Hypotheses

As already discussed, the extant literature shows that network centrality affects the success of startups and established firms both in the funding and the aftermarket phase (see Section 2.2.1). However, little is known about the impact of social networks on longer-term market performance in the context of early-stage ventures. We extend the existing empirical evidence and analyse the impact of network structures on the market valuation and liquidity of token-financed ventures.

Ventures obtaining funding through token offerings are represented by an extended team composed of founders, developers, and managers. Typically, they are assisted by an advisory committee. In line with prior research, we define the venture team as all individuals who actively work on the development and implementation of potential future products funded by a token offering. We differentiate between a venture's team and advisor network to investigate the related effects of connectedness separately for several reasons. We assume that venture team members, i.e., founders, developers, and managers, aim for long-term success of the project. They generated the initial idea of the project and remain actively involved and incentivized to develop a valuable venture after the token offering ends. In contrast, the advisor team usually has no meaningful connection to the organization and is primarily responsible and remunerated to share their expertise and promote the projects in the fundraising phase. This naturally implies that the stakeholder group of advisors is less involved in the venture's daily operating business and progress, but merely provides guidance to several other ventures consecutively or even at the same time.[7] Liu et al. (2021) provide evidence that hiring experts as advisors is associated with a higher likelihood of fundraising success, but not with a higher chance of token exchange listing and one-year survival. Related to that, Giudici et al. (2020) show that advisor centrality is positively related to the funding success of token offerings.[8] However, due to their different compensation structure and incentives to contribute to the long-term success of the business, it is plausible to assume that only team networks provide a credible signal for a venture's quality and help reduce information frictions in the aftermarket. By distinguishing the effects of team and advisor centrality, we follow research that considers founder, investor, and board networks separately (Witt (2004), Harris and Helfat (2007), Cohen et al. (2008), Nguyen (2012), Larcker et al. (2013), Ozsoylev et al. (2013), Bajo et al. (2020), Zheng et al. (2020)).

Signalling allows transferring information about the quality of a venture to potential investors, which is particularly important for the functioning of capital markets in environments prone to asymmetric information and moral hazard (Campbell and Kracaw (1980), Healy and Palepu (2001)). Since ventures seeking funding via token offerings are typically in their very early stages, information on the intentions and quality of a venture is scarce (Chen (2019), Fisch (2019), Howell et al. (2019)). Facing uncertainty in the quality of knowledge, investors look for signals that ascertain or certify quality (Tversky and Kahneman (1974)). We argue that venture social capital, the position of a venture's team in the overall network, provides such a signal, i.e., it implies a signal about the quality of the project both in the funding and the post-funding phase. Therefore, potential investors face a lower degree of information asymmetry about investment targets that credibly offer such a signal. Momtaz (2021a) argues that signals that successfully provide information about a venture's abilities determine whether potential contributors assign a valuation premium (positive signals) or a valuation discount (negative signals) to the venture. Empirical evidence confirms that generating valuable signals is crucial for fundraising success (Chen (2019), Mansouri and Momtaz (2022)). Investors are able to directly assess the centrality of prospective investment target teams as crypto platforms provide detailed information about the ventures' team affiliations, i.e., individuals' track record and ties to other ventures. We refer to this signal related to team network centrality as the *certification benefit*.

We further argue that leveraging venture teams' relational ties and network positions contributes to reduce information asymmetry because information relevant for venture success is transmitted more efficiently across networks (Chuluun et al. (2017)). We refer to the associated ease of information transmission from a privileged position in the network and the resulting valuation implications as the *connection premium*. In the funding phase, individuals can quickly build a network of weak ties from casual acquaintances. However, according to Dubini and Aldrich (1991), long-term networks are built upon strong ties, and the creation of strong ties involves repeated interactions and expanding one's circle of trust (Coleman (1988)). Trust is purely enhanced through self-interest as people expect that there is a good chance of dealing with each other again. Long-term relations also reduce uncertainty about whether the other party will directly or indirectly assist in the future. In particular, when relations are implicitly long-term, individual actors in the network will more likely raise their voice rather than exit when unhappy with the direction a venture is taking. Central teams have a particularly important role in facilitating the information exchange with other connected ventures. We thus assume that only networks characterized by strong and long-term relationships of trust facilitate information flows and provide a *connection premium* that positively affects a venture's success in the long-run.

All these arguments for a *certification benefit* and a *connection premium* suggest that a team's network centrality is positively correlated with venture success in the post-funding stage. A venture's privileged position in the network via its team members sends a credible signal and reduces the costs of information acquisition. Access to information through an informal network is particularly important in situations when public information that is relevant for the venture's success is not available. For example, in the absence of tangible information such as informative white paper documents, the possibility of more central team members to access superior information through their network should be most valuable and have a particularly strong influence on venture success in the post-funding phase. This may lead to a substitution effect between informal information dissemination within networks and more formal information contained in published white paper documents. Overall, these arguments lead to the following testable hypotheses:

Hypothesis (H1): *Team network centrality is positively related to venture success in the post-funding phase.*

Hypothesis (H2): *The positive relation between team network centrality and venture success is stronger if tangible information is limited.*

These hypotheses crucially depend on the definition of network centrality. So far, we have only loosely described this concept as interpersonal connections. In the next section, we provide an in-depth explanation of the underlying data and formulas to calculate centrality on venture level.

2.4 Methods

2.4.1 Sample and data

Our sample is built on commonly used data sources from the token offering literature.[9] Firstly, we obtain primary market data from the token offering listing site *ICObench* (`www.icobench.com`).[10] The initial sample is based on token offerings with a fundraising start date between August 2015

Table 2.1
Sample selection
This table summarizes the selection of our main analysis sample described in Section 2.4.1.

Description	Obs.
+ Token offerings starting between August 2015 and September 2018	3,630
– Ventures without successful funding or data on fundraising success	2,312
– Ventures without team *LinkedIn* data required for human capital control variables	299
– Ventures without exchange listing data from *Coinmarketcap*	675
– Ventures listed under 3 months or with insufficient trading data from *Coinmarketcap*	215
Final sample	129

and September 2018. We complement deal data with further venture level controls from ventures' websites and social media profiles. The information on open-sourced code stems from *GitHub*. Information whether bonus or bounty programs to promote the token offering are available is obtained from various sources (ventures' websites, white papers, social media channels and further token offering listing sites such as *Coinschedule, CoinGecko* and *ICOalert*). Using this approach, we are able to identify an initial sample of 1,019 token offerings with complete information.

Secondary market data for exchange-listed tokens stem from *Coinmarketcap*, being the most established source for post-funding performance data (Fisch (2019), Lyandres et al. (2022), Momtaz (2021b)). While we retrieve all performance data available until July 2019, the subsample of ventures with aftermarket data reduces to 739 sample ventures listing their tokens as of July 2019 and trade at least for three months. We restrict the start of our aftermarket sample to October 2017 as the token offering market was in its infancy and venture networks were dominated by few (166) still fairly disconnected ventures potentially distorting our results.

Team member and advisor attributes are sampled from their *ICObench* and *LinkedIn* profiles. After retaining firms with non-missing observations on team member and advisor characteristics, the final sample includes 1,170 month-year observations from 129 ventures, with listed tokens as of October 2017 until July 2019, involving 1,548 individual team members and 496 advisors. The significant reduction in sample size is common for studies conducting research on post-funding performance data in the token offering market. The initial sample size of related studies on aftermarket performance reduces similarly (Fisch and Momtaz (2020), Lyandres et al. (2022)). In line with prior research on token offerings, we winsorize all continuous variables at the 5^{th} and 95^{th} percentiles to constrain the influence of outliers. Table 2.1 summarizes the sample selection.

2.4.2 Variables

The goal of our study is to shed light and extend prior work (see Section 2.2) on the determinants of outcome[11] variables of entrepreneurial ventures that can broadly be categorized into venture success indicators. Following prior post-funding research in the IPO and token offering literature, the two dependent variables in our empirical analysis of post-funding venture success are the token trading volume ($Trading\ volume$) and the market-to-book ratio ($Market-to-book$).

As shown in existing work on the aftermarket performance of ventures funded via token offerings, token trading volume is log-normally distributed, with a few high-value observations (Howell et al. (2019), Lyandres et al. (2022)). We operationalize token liquidity by computing the total logarithmic monthly trading volume in USD reported on *Coinmarketcap*. $Market-to-book$ is also measured on a monthly basis and is defined as the unitary token price multiplied by the circulating token supply relative to the ventures' size, defined as the logarithmic funding amount in USD collected via the token offering (Fisch (2019), Mansouri and Momtaz (2022)). All variables are obtained by merging several data sources. Historic trading volumes and token prices converted into USD stem from *Coinmarketcap*. Funding amounts are collected from *ICObench* and venture websites. As some ventures only accept cryptocurrency in exchange for tokens, we convert all funding amounts to USD based on the quoted exchange rate on *Coinmarketcap* at the start date of the token offering.

Table 2.2 describes our sample ventures. Panel A shows that the average sample venture yields $30.4 million logarithmic monthly trading volume, with a standard deviation of $24.4 million. The average venture exhibits a market-to-book ratio of 5.0, with a monthly standard deviation of 3.0. Overall, our summary statistics are comparable to other related studies (Fisch (2019), Colombo et al. (2022), Florysiak and Schandlbauer (2022), Mansouri and Momtaz (2022)).

2.4.2.1 Outcome variables

2.4.2.2 Independent variables

To measure the information flows and the quality of relationships in our research setting, we borrow from social network theory (Freeman (1978)). The key aim of social network analysis is to identify influential actors, measured by how "central" an actor is positioned in the network, from the relationships existing among a set of economic actors. Social network analysis utilizes graph theory to illustrate the concept of centrality (Wasserman et al. (1994)). As an example, the network shown in

Table 2.2
Summary statistics

This table provides descriptive statistics for the main outcome and control variables used in this study. It reports the mean, the median, the standard deviation (SD), the 25th (P25), 75th (P75) percentile and the number of observations (N). All continuous variables are winsorized at the 5% and 95% tails to constrain for the impact of outliers. For a detailed description of underlying data, see Table A1 in the appendix.

	Mean	Median	SD	P25	P75	N
Panel A: Venture post-funding success						
Trading volume	30.393	32.727	24.401	12.000	48.954	1,170
Market-to-book	5.022	2.961	5.290	0.998	7.134	1,162
Panel B: Market characteristics						
Volatility	0.089	0.076	0.046	0.059	0.103	1,170
Price (log)	0.396	0.184	0.472	0.052	0.580	1,170
Bitcoin price ($k)	7.557	7.300	2.493	6.484	9.012	1,170
Panel C: Human capital characteristics						
Team size	12.000	10.000	7.416	7.000	16.000	129
Advisor size	3.845	3.000	4.227	0.000	7.000	129
Technical experience (dummy)	2.659	2.000	2.635	1.000	4.000	129
Industry experience (dummy)	3.434	3.000	3.064	1.000	5.000	129
PhD (dummy)	0.349	0.000	0.478	0.000	1.000	129
Success index	2.093	1.000	4.208	0.000	2.000	129
Panel D: Venture characteristics						
Blockchain (dummy)	0.581	1.000	0.495	0.000	1.000	129
Open source (dummy)	0.930	1.000	0.256	1.000	1.000	129
Industries	2.341	2.000	1.400	1.000	3.000	129
Size (log)	2.868	3.020	0.820	2.303	3.526	129
Panel E: Fundraising characteristics						
Token supply	12.013	17.727	9.520	0.000	19.808	129
Competition	112.620	122.000	70.741	54.000	161.000	129
Duration (days)	21.674	14.000	38.002	1.000	30.000	129
Platform (dummy)	0.922	1.000	0.268	1.000	1.000	129
Airdrop (dummy)	0.465	0.000	0.501	0.000	1.000	129
Pre-sale (dummy)	0.264	0.000	0.442	0.000	1.000	129
Bonus program (dummy)	0.279	0.000	0.450	0.000	1.000	129
KYC process (dummy)	0.093	0.000	0.292	0.000	0.000	129
Investor registration (dummy)	0.016	0.000	0.124	0.000	0.000	129
Hardcap (dummy)	0.628	1.000	0.485	0.000	1.000	129
Softcap (dummy)	0.302	0.000	0.461	0.000	1.000	129
Video (dummy)	0.814	1.000	0.391	1.000	1.000	129

Figure 2.1 depicts team member relationships among ventures that have conducted a token offering by October 2018. The ventures are represented as nodes, and edges represent the ties among them, created by their team members. Visually, it appears that seven ventures are the most "central" in this network, in the sense that they are connected to the largest number of team members from other ventures. In graph theory, a network is represented by the ties among the actors of the network, the square "adjacency" matrix. To construct our bipartite network, we build node lists of team members (15,206), advisors (7,167) and ventures (2,058). Team member and advisor nodes are connected by

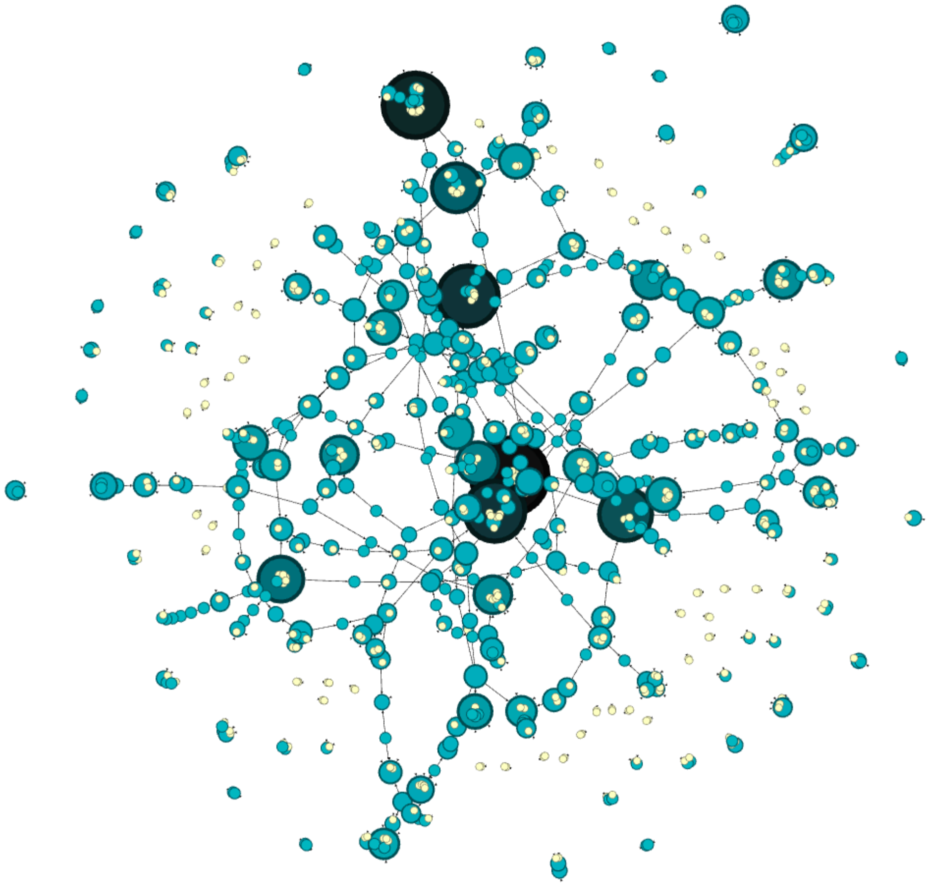

Figure 2.1. Venture team network as of October 2018. This graphic illustrates the structure of the network of relationships between venture team members that currently participate in at least one venture as of October 2018. Two ventures are linked if at least one team member participates in the same venture at the same time. Larger nodes denote higher degree centrality, that is, more simple connections between team members of the venture.

an undirected and unweighted link whenever there is a collegial relationship within a venture, i.e., they are listed as a team member or advisor on the venture's *ICObench* profile at the same time.

Networks are not static. Relationships change by entry and exit of individuals, thereby altering each venture's centrality. As sufficient data on which date a person exactly starts or ends her role in the respective venture is not available, once created, links persist and become part of the network over the lifetime of the venture. Using this approach, we construct networks and calculate centrality measures for both groups, team members and advisors, in each month t. We define the first month of a token offering as the starting point of the respective connection. We exclude ventures from the network that do not succeed to list their tokens on *Coinmarketcap* within one year after the token offering ends. In addition, we require tokens to be traded above a minimum threshold of $1,000 per quarter to maintain their membership in the network.

Social network analysis provides multiple metrics that enable us to uncover different aspects of individuals' (e.g. team members or advisors) positions in the overall network (Borgatti (2005)). In our empirical analysis we introduce four different network centrality measures commonly applied in related literature: (i) $DEGREE$ centrality, (ii) $EIGENVECTOR$ centrality (Bonacich (1987)), (iii) $BETWEENNESS$ centrality (Freeman (1978)) and (iv) $CLOSENESS$ (Freeman (1978)).

Computing $DEGREE$ centrality, we count the number of links between one actor and others. Individuals more closely connected to others are likely to hold a more privileged position within the venture network. Formally, the $DEGREE$ centrality of a person i in month t is defined as:

$$DEGREE_{it} = \sum_{j \neq i}^{N_t} x_{it}, \tag{2.1}$$

where N_t is the number of nodes in the network in month t, and x_{it} equals one if two nodes (i.e., team members) are connected by an edge (i.e., common team members) in month t.

Since $DEGREE$ centrality is dependent on the number of existing nodes, i.e., other team members or advisors in the network, this may create a time-bias in time-series analysis (Bajo et al. (2020)). As outlined in Section 2.2.2, the dramatic increase of ventures aiming for funding via token offerings in 2017 and 2018 indicates that the network potential increases substantially. To accommodate for this potential bias, where the maximum number of possible connections rises from, e.g., 3,148 in October 2017 to 21,691 in August 2018, we follow Bajo et al. (2020) and use $N - 1$ as a normalizing factor to calculate the normalized version of $DEGREE$ centrality:

$$N\_DEGREE_{it} = \frac{\sum_{j \neq i}^{N_t} x_{it}}{N_t - 1}. \tag{2.2}$$

The N_DEGREE centrality ranges from 0 to 1; it measures the percentage of the highest possible number of connections a person maintains in each month t. A value of zero implies no connections to others, while a value of one indicates direct connections to all network actors.

A simple count of connections of degree centrality as a local centrality measure does not necessarily represent the importance of an individual within the network. If many connections to other less connected actors exist, this individual's influence and importance in the personal network may be somewhat limited. Therefore, we employ $EIGENVECTOR$ centrality (also known as *prestige score*) as a variation of $DEGREE$ centrality. $EIGENVECTOR$ accords each vertex x_{ijt} a centrality depending on the number and quality of its connections, i.e., a smaller number of high-quality contacts may outrank a larger number of mediocre contacts because these have a lower relative importance in the network. Formally, we calculate:

$$EIGENVECTOR_{it} = \lambda \sum_{j \neq i}^{N_t} x_{ijt} e_{jt}, \tag{2.3}$$

where λ is a constant to prevent non-zero solutions, and e_{jt} is the eigenvector centrality score (Bonacich (1972), Bonacich (1987)). Analogous to our first network measure, *DEGREE* centrality, we follow Bajo et al. (2020) and scale *EIGENVECTOR* by the maximum possible value for the N actor network in month t.

Our third measure of network centrality, *BETWEENNESS*, captures the extent to which a node plays a bridging role in a network. Assigning a higher score to nodes linking more pairs of other nodes, i.e., lying on a higher number of shortest paths, *BETWEENNESS* centrality departs from the above concept of *DEGREE* and *EIGENVECTOR* centrality. As outlined in Burt's (2004) theory of structural holes, the lack of relationships among a newly forming community gives actors positioned in structural holes a strategic benefit, such as control, access to novel information, and resource brokerage. Nodes that fill a structural hole are attractive relationship partners because they connect other nodes that otherwise would be less connected by forming non-redundant, often weak ties in the network. The more nodes depend on a node's connections with others, the higher the *BETWEENNESS* centrality becomes. Therefore, *BETWEENNESS* centrality can be defined as the ratio of the shortest paths between all node pairs in a network passing through node i, divided by the number of alternative shortest paths. Formally, the *BETWEENNESS* centrality of person i in month t is given by the expression:

$$BETWEENNESS_{it} = \sum_{j \neq i \neq z}^{N_t} \frac{b_{jzt}(i)}{b_{jzt}}, \tag{2.4}$$

where $b_{jzt}(i)$ is the number of the shortest paths between nodes j and z passing i in month t, and b_{jzt} is the total number of shortest paths between j and z in month t.

Finally, to detect nodes which can spread information efficiently through a graph and proxy for the speed with which information can be obtained from the network, we introduce *CLOSENESS* centrality as another network centrality measure. *CLOSENESS* centrality measures the length of the shortest paths from node i to all other nodes. Since the sum of distances depends on the number of nodes in the network, $CLOSENESS$ is expressed as the normalized inverse of the sum of topological distances in the graph. Formally, we define $CLOSENESS$ centrality as:

$$CLOSENESS_{it} = \frac{N_t - 1}{\sum_{j \neq i}^{N_t} d_{izt}}, \tag{2.5}$$

where d_{izt} is the length of the shortest path between nodes i and z in the network in month t.

In the next step, we follow Larcker et al. (2013) and run a principal component analysis of the four centrality measures N_DEGREE, $EIGENVECTOR$, $BETWEENNESS$ and $CLOSENESS$; the first principal component captures nearly 83% of the variation in our centrality measures. Therefore, we interpret the first principal component as a suitable measure to define "overall" well-connectedness. For our main analyses, we aggregate the predicted monthly values of all venture team members and advisors separately to the venture level.[12]

While we apply standard network measures, it should be noted that our modeling of venture level networks is based on several implicit assumptions. Following Larcker et al. (2013), we presuppose that the links between ventures represent the primary channel of social, informational, and resource exchange between venture team members and advisors. It is still possible that individual networks are formed outside "formal" team meetings and venture operations, which means they are defined by "informal" social and non-professional connections. As Westphal et al. (2006) and Hwang and Kim (2009) suggest, because they are positively correlated, formal and informal networks can be strategically complementary. Moreover, two of our network measures, $BETWEENNESS$ and $CLOSENESS$, implicitly assume that information and resources flow through the network along the shortest possible path. However, Borgatti (2005) and Borgatti and Everett (2006) criticize that the shortest path may not always capture the true flow of information and resources.

Over our sample period, the token offering market experienced substantial entry and exit, which has led to a considerable reordering of relationships. We construct a new network for each month t, using data on token offerings trading in t to capture the dynamics of these relationships. We then use the resulting adjacency matrices in each month to construct the four centrality measures as described above. All measures for the subsample of ventures with the required minimum level of trading activity are summarized in Table 2.3.

Table 2.3
Network characteristics

This table provides descriptive statistics for the main explanatory variables used in this study. It reports the mean, the median, the standard deviation (SD), the 25th (P25), 75th (P75) percentile and the number of observations (N). All continuous variables are winsorized at the 5% and 95% tails to constrain the impact of outliers. For a detailed description of underlying data, see Table A1 in the appendix.

	Mean	Median	SD	P25	P75	N
Panel A: Team network characteristics						
Team centrality	0.888	0.940	0.425	0.698	1.193	1,170
Team degree	0.858	0.539	0.957	0.221	1.105	1,170
Team betweenness	0.135	0.000	0.216	0.000	0.203	1,170
Team closeness	0.029	0.022	0.031	0.001	0.051	1,170
Team eigenvector	0.006	0.000	0.041	0.000	0.000	1,170
Panel B: Advisor network characteristics						
Advisor centrality	0.739	0.406	0.385	0.406	1.120	574
Advisor degree	0.781	0.568	0.696	0.347	1.052	574
Advisor betweenness	0.479	0.224	0.676	0.000	0.584	574
Advisor closeness	0.026	0.023	0.021	0.006	0.042	574
Advisor eigenvector	0.000	0.000	0.001	0.000	0.000	574

Whilst the values of $EIGENVECTOR$, $BETWEENNESS$ and $CLOSENESS$ do not have an immediate economic interpretation, the level of N_DEGREE is a more intuitive concept. While the average (median) venture team is connected with 0.9 (0.5) percent of the maximum theoretical number of connections, the average (median) advisor team exhibits normalized degree centrality of 0.8 (0.6) percent. All network measures exhibit a fair degree of variation, suggesting that the positional advantage of individual ventures caused by the network of their team members and advisors is unequally distributed in our networks.

2.4.2.3 Control variables

To rule out confounding influences on venture success, we include several control variables commonly applied in the recent token offerings literature (Fisch (2019), Howell et al. (2019), Fisch and Momtaz (2020), Benedetti and Kostovetsky (2021)). Individual variables are selected to control for (i) the prevailing market sentiment, (ii) venture human capital, (iii) structural characteristics of the venture as well as (iv) the characteristics of the token offering itself. For brevity, detailed definitions of all control variables are provided in Appendix Table A1. Summary statistics shown in Panels B-E of Table 2.2 indicate that all control variables are in line with existing literature.

2.4.2.4 Moderating variables

Our research joins the burgeoning entrepreneurial finance literature that examines the role of information asymmetry on venture success. Several studies relate to white paper content as a proxy for information asymmetry and test predictions of adverse selection and signalling in the token offering market (Fisch (2019), Samieifar and Baur (2021), Florysiak and Schandlbauer (2022), Thewissen et al. (2022)). In the course of a token offering, ventures typically publish a white paper on their website or listing sites such as *ICObench.* White papers are the primary tool for ventures to describe the project, the business idea, the team, and the underlying technology to potential investors and to promote the funding campaign. Florysiak and Schandlbauer (2022)'s empirical results suggest that high-quality ventures signal their quality by providing more informative white paper content. Accordingly, Florysiak and Schandlbauer (2022) measure the signalling efforts of the token offering phase using differences in their textual white paper information content.

To test whether the availability of tangible information moderates the effect of team networks on post-funding success, we borrow from Florysiak and Schandlbauer (2022) and relate their measure of white paper information content to team centrality.[13]

Using their data on white paper information content, we define $Low\,WPIC\,(focal\,venture)$ as a dummy indicator that takes the value of 1 if a venture's white paper provides additional information in comparison to its industry peers' white papers below the 10$^{\text{th}}$ percentile, and 0 otherwise. In addition, we construct the dummy indicator $High\,WPIC\,(connected\,ventures)$, which takes the value of 1 if the average information content of white papers distributed by the focal venture's connected ventures is above the 90$^{\text{th}}$ percentile. Interacting these dummy variables with our centrality measures allows us to test whether informal information dissemination within networks substitutes more tangible information about a venture in published white papers.

2.4.3 Econometric approach

To test our main Hypothesis 1, suggesting that higher levels of team centrality are associated with improved venture performance, we estimate several specifications of the following regression:

$$DV_{it} = \beta \times Team\,centrality_{it-1} + \gamma \times \Omega_{it-1} + FEs + \varepsilon_{it}, \tag{2.6}$$

where DV_{it} refers to our two dependent (outcome) variables describing venture success in the post-funding phase; $Team\,centrality_{it-1}$ is the principal component of the four normalized centrality measures N_DEGREE, $EIGENVECTOR$, $BETWEENNESS$ and $CLOSENESS$ over all currently engaged team members in venture i in month $t-1$; and Ω_{it-1} is a vector of control variables.

In a first step, we examine how a venture's monthly trading volume ($Trading\,volume_{it}$) responds to variations in monthly team centrality ($Team\,centrality_{it-1}$). In a second step, we relate our monthly team centrality measure to the venture's average monthly market-to-book ratio ($Market\!-\!to\!-\!book_{it}$). Next, we examine the relation between team centrality, the quality of white paper information content, and our two measures of venture success in the post-funding phase. In a robustness test, we analyse the impact of advisor centrality ($Advisor\,centrality_{it-1}$) on venture aftermarket success.

The control variables applied in all our regressions are related to the prevailing market sentiment and commonly applied market controls, venture human capital characteristics, and structural characteristics of the venture as well as the token offering itself.

FEs are month-year fixed effects and country fixed effects. To keep with previous studies (Fisch and Momtaz (2020), Bellavitis et al. (2022), Mansouri and Momtaz (2022)), we introduce these FEs throughout our analyses to control for cycle-related effects and geographical variation in the token offering market. All reported standard errors are robust.

As in related entrepreneurial finance studies (Colombo and Grilli (2010), Bertoni et al. (2011), Fisch and Momtaz (2020), Sun et al. (2020), Mansouri and Momtaz (2022)), endogeneity is a concern in our empirical framework. We are interested in the treatment effect of team (and advisor) centrality on ventures' aftermarket performance. To address the econometric issue of reverse causality, i.e., that already highly valuable ventures attract teams (or advisors) with extensive network relationships, we avoid simultaneity by regressing contemporaneous values of DV on one-month lagged values of $Team\,centrality_{it-1}$ (or $Advisor\,centrality_{it-1}$) and our set of control variables (Ω_{it-1}; see Equation 2.6).

To mitigate remaining doubts about violations of the exogeneity condition (i.e., $E[\Omega_{it-1}, \varepsilon_i] \neq 0$), we address sample selection bias by controlling for selection based on observed and unobserved heterogeneity.[14] Both techniques require a selection model. For this purpose, we sort all values of $Team\,centrality$ (or $Advisor\,centrality$) in our sample by month-year to distinguish between ventures with highly versus barely central team members (advisors) based on the median, resulting in a $High\,centrality_{it}$ dummy variable. Using a probit model, we model the probability that venture i belongs to the subsample of high centrality firms in month t. The independent variables in this model are captured by a vector of exogenous market and individual venture characteristics ($\Omega^{(s)}_{it-1}$). Formally, we estimate the following first-stage probit model:

$$High\,centrality_{it} = \delta\Omega^{(s)}_{it-1} + \xi_{it}. \tag{2.7}$$

These "selection probabilities" are then transformed and included in our second stage models, which estimate the treatment effect of team (advisor) centrality on venture success. Following the entrepreneurial literature (Colombo and Grilli (2010), Sun et al. (2020), Mansouri and Momtaz (2022)), we adapt a Heckman correction model (Heckman (1979)) to address sample selection bias. We obtain the predicted individual probabilities from Equation 2.7 and compute inverse Mills ratios (IMRs) for the selection of ventures into a highly central position into the overall network:

$$IMR_{it} = \frac{\phi(\frac{\delta\Omega^{(s)}_{it}}{\sigma_{\xi_{it}}})}{\Phi(\frac{\delta\Omega^{(s)}_{it}}{\sigma_{\xi_{it}}})}, \tag{2.8}$$

where IMR_{it} is the IMR of venture i in month t; and $\phi(.)$ and $\Phi(.)$ are the probability density and the cumulative density of the standard normal distribution, respectively. The one-month lagged IMR is then incorporated as an additional explanatory variable into the baseline model in Equation 2.6 to partial out a possible selection effect λ. Formally, we estimate:

$$DV^{IMR}_{it} = \beta Team\,centrality_{it-1} + \lambda IMR_{it-1} + \gamma\Omega_{it-1} + FEs + \upsilon_{it}. \tag{2.9}$$

Our alternative second-stage approach controls for "selection on unobservables" by using an adjusted instrumental variables approach. Consistent with Gourieroux et al. (1987), Colombo and Grilli (2005), and Mansouri and Momtaz (2022), we define the generalized residual for venture i at time t, GR_i, as:

$$GR_{it} = High\,centrality_{it} \times \frac{\phi(-\delta\Omega^{(s)}_{it})}{1-\Phi(-\delta\Omega^{(s)}_{it})} + (1 - High\,centrality_{it}) \times \frac{-\phi(\delta\Omega^{(s)}_{it})}{\Phi(-\delta\Omega^{(s)}_{it})}, \tag{2.10}$$

and use it as an instrument for venture centrality in our baseline regression in Equation 2.6.

Next, to test Hypothesis 2, we reiterate estimating Equation 2.6–Equation 2.10. In particular, we include our two measures of white paper information content from Florysiak and Schandlbauer (2022), $Low\,WPIC\,(focal\,venture)$ and $High\,WPIC\,(connected\,ventures)$, and interact these indicator variables with the $High\,team\,(centrality)$ dummy variable. In particular, examining the moderation effect of white paper informativeness on the aftermarket performance-centrality relationship, we estimate the following extended regression model:

$$\begin{aligned} DV_{it} = \beta \times High\,team\,centrality_{it-1} + \theta \times High\,team\,centrality_{it-1} \\ \times Low\,WPIC_{it-1} + \gamma \times \Omega_{it-1} + FEs + \rho_{it}, \end{aligned} \tag{2.11}$$

where $Low\,WPIC\,(focal\,venture)$ takes the value of 1 if a venture's white paper provides additional information in comparison to its industry peers' white papers below the 10^{th} percentile, and 0 otherwise. In an alternative model specification, we also interact the dummy indicator for $High\,team\,centrality$ with the dummy for $High\,WPIC\,(connected\,ventures)$, which that takes the value of 1 if the average information content of white papers distributed by the focal venture's connected ventures is above the 90^{th} percentile, and 0 otherwise.

2.5 Empirical results

2.5.1 Venture team centrality and post-funding success

Our main hypothesis is that that ventures with more central team members are associated with better post-funding venture success. Central team members are able to provide credible signals to the market and reduce information asymmetries.

Table 2.4 presents the results for our baseline regressions. As outlined in Section 2.4.3, we address concerns about the selection of ventures into highly connected, i.e., central, teams by implementing a two-stage Heckman correction model and an instrumental variable approach. Column (1) estimates the first-stage of the correction model (see Equation 2.7) and explains the probability that venture i belongs to the subsample of ventures with above-median team centrality in month t. For example, we find that ventures with at least one team member who has already successfully conducted a token offering attract more highly central team members. The predicted individual probabilities can be used to compute inverse Mills ratios (IMRs) and generalized residuals (GRs).

In columns (2) and (3), the dependent variable is our first proxy for post-funding venture success, $Trading\,volume$. As expected, our measure of $Team\,centrality$ is positively related to ven-

Table 2.4
Venture team network and liquidity

This table reports estimation results from regressions of venture liquidity on team centrality, and control variables. Liquidity is the natural logarithm of the total monthly trading volume reported on *Coinmarketcap*. Team centrality is expressed as the aggregated monthly normalized PCA centrality over all team members included in the *ICObench* database and trading on *Coinmarketcap* between October 2017 to July 2019. Column (1) estimates the first-stage Heckman correction model (see Equation 2.7). Model (2) applies team centrality as explanatory variable. Column (3) adds further controls for characteristics following existing IPO and token offering literature. Column (4) shows the results of the Inverse Mills Ratio (IMR) approach. Column (5) uses the generalized residuals (see Equation 2.10) as an instrumental variable (IV) for high team centrality. Model (6) - (9) follow the same approach exchanging team centrality for a dummy variable indicating whether venture *i* exhibits above median team centrality or not. To avoid simultaneity, we regress contemporaneous values of the dependent variables on one-month lagged explanatory variables in all our regression analyses. All specifications include country and month-year fixed effects. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For a detailed description of underlying data, see Table A1 in the appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model:	Selection	Main		IMR	IV	Main		IMR	IV
Dependent variable:	$1_t^{\text{High-centrality}}$	Trading volume$_t$							
Team centrality$_{t-1}$		4.275^{**}	3.891^{**}	4.509^{**}	7.302^{**}				
		(1.729)	(1.862)	(1.939)	(2.963)				
High team centrality (dummy)$_{t-1}$						3.889^{***}	4.259^{***}	4.676^{***}	3.872^{**}
						(1.401)	(1.563)	(1.608)	(1.564)
Market characteristics:									
Volatility$_{t-1}$	-0.074		13.252	12.964	13.440		13.726	13.455	13.663
	(1.382)		(20.433)	(20.370)	(19.982)		(20.448)	(20.363)	(19.661)
Price (log)$_{t-1}$	-0.298^{**}		14.085^{***}	12.974^{***}	14.116^{***}		14.507^{***}	13.380^{***}	14.466^{***}
	(0.125)		(1.756)	(1.938)	(1.694)		(1.762)	(1.916)	(1.701)
Bitcoin price ($k)$_{t-1}$	-0.366^{***}		14.343^{***}	12.743^{***}	15.248^{***}		14.092^{***}	12.318^{***}	14.021^{***}
	(0.110)		(2.868)	(3.089)	(2.794)		(2.822)	(3.075)	(2.723)
Human capital characteristics:									
Team size	0.000		-0.113	-0.023	-0.120		-0.111	-0.019	-0.111
	(0.011)		(0.165)	(0.168)	(0.160)		(0.164)	(0.166)	(0.158)
Technical experience (dummy)	0.157^{***}		1.105^{**}	1.460^{***}	1.017^{**}		1.058^{**}	1.433^{***}	1.071^{**}
	(0.029)		(0.443)	(0.519)	(0.432)		(0.439)	(0.516)	(0.424)

(*continued*)

Table 2.4 — *continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model:	Selection	Main		IMR	IV	Main		IMR	IV
Dependent variable:	$1_t^{\text{High-centrality}}$	Trading volume$_t$							
Industry experience (dummy)	-0.300***		-1.018***	-1.802**	-0.834**		-0.913***	-1.740**	-0.941***
	(0.025)		(0.344)	(0.703)	(0.353)		(0.343)	(0.699)	(0.332)
PhD (dummy)	-0.210*		5.425***	4.723**	5.871***		5.091***	4.286**	5.075***
	(0.128)		(1.863)	(1.892)	(1.838)		(1.827)	(1.865)	(1.763)
Success index	0.261***		-0.367	0.101	-0.509*		-0.391	0.110	-0.374
	(0.029)		(0.292)	(0.517)	(0.289)		(0.283)	(0.515)	(0.277)
Venture & fundraising controls	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time & country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.342	0.308	0.420	0.421	0.418	0.310	0.422	0.424	0.422
Adjusted R-squared	n/a	0.273	0.375	0.376	0.373	0.275	0.378	0.379	0.378
Observations	1,170	1,011	1,011	1,011	1,011	1,011	1,011	1,011	1,011

tures' trading volume. To confirm that the team centrality-venture success relationship is not merely driven by the presence of our control variables, column (2) presents the results of a control model, including only $Team\,centrality$ and the FEs. In both models, the coefficient of $Team\,centrality$ is statistically significant at the 5% level. In economic terms, and taking column (2) as the example, a one unit increase in team centrality leads to 4.3% increase in monthly trading volume.

To address the potential selection bias, we estimate in column (4) the second-stage Heckman correction model (Equation 2.9). The positive coefficient on $Team\,centrality$ increases in magnitude, and the estimate of IMR is statistically insignificant (not reported). This suggests that "selection on observables" does not bias the economically important effect of $Team\,centrality$ on $Trading\,volume$. Using the GR as an instrumental variable for team centrality in column (5), the estimated coefficient of $Team\,centrality$ increases to 7.302. In this case, a one unit increase in team centrality increases the average monthly trading volume of \$30.4 million by as much as \$2.1 million.

In an alternative model specification, to rule out that outliers are driving our results, we resort to a dummy variable approach. We rerun the baseline regression using the $High\,team\,centrality$ dummy variable, which takes the value of 1 if the team's position in the network in month t is above the sample median, and 0 otherwise. The results in columns (6) to (9) confirm the positive and statistically significant trading volume-team centrality relationship in all models.

For the control variables, we find largely consistent parameter estimates throughout all regression specifications. In particular, the prevailing market sentiment (i.e., token and Bitcoin price level), technical team experience, and teams with PhDs positively relate to trading volume. Perhaps surprisingly, team size, blockchain industry experience and the number of prior successful token offerings throughout all team members are mostly unrelated to token liquidity.

As another measure for post-funding success, we compute the average $Market\!-\!to\!-\!book$ in each month after the initial listing. Table 2.5 shows the results from re-estimating the baseline model when using $Market\!-\!to\!-\!book$ as the dependent variable. Analogous to our findings above, $Team\,centrality$ is positively and significantly related to $Market\!-\!to\!-\!book$. In other words, the second-stage results in columns (2) to (9) confirm that a venture's team network is positively associated with aftermarket success. Moreover, the estimated coefficients of $Team\,centrality$ are of similar magnitude, ranging between 0.739 and 1.405 (statistically significant at least at the 5% confidence level). In turn, this corresponds to increases in venture value between 6.3% and 11.9% in response to a one-standard deviation increase in $Team\ centrality$ relative to the sample mean.[15] Compared to the average $Market\!-\!to\!-\!book$ ratio of 5.0, these marginal effects are clearly economically relevant.

Overall, our results are robust to controlling for both observed and unobserved heterogeneity in all different model specifications. The evidence strongly supports Hypothesis 1, suggesting that more central team members are positively related to venture success in the post-funding phase, as measured by trading liquidity and token market value.

2.5.2 Information availability and venture team centrality

In Hypothesis 2, we posit that the aftermarket success-team centrality relationship is likely to be moderated by the availability and quality of tangible information. Therefore, we sequentially add the dummy variables $Low\ WPIC\ (focal\ venture)$ and $High\ WPIC\ (connected\ ventures)$ as well as their interaction terms with $High\ team\ centrality$ to the baseline model. Table 2.6 presents the regression results for both post-funding success measures, i.e., trading volume and the market-to-book ratio.

For the sake of brevity, we focus on the IMR (Equation 2.9) and the IV model specifications (Equation 2.10) in Table 2.6. Columns (1) to (4) show the regression results using $Trading\ volume$ as the dependent variable. Compared with our baseline model in Table 2.4, the estimated coefficients of $High\ team\ centrality$ in columns (1) and (2) decrease slightly but remain statistically significant. Most importantly, if the white paper of the focal firm is less informative ($Low\ WPIC\ (focal\ venture)$), serving as a measure for the poor quality of information shared with investors in the funding phase, the interactions of $High\ team\ centrality$ are significantly positive at the 5% level.

These results provide evidence for a substitution effect between informal information dissemination within networks and more tangible information in published white papers. When team centrality is higher, formal information quality is less important for investors, and vice versa. In other words, investors' trading activity and post-funding performance increase sharply with the presence of teams that are centrally positioned in the entire venture network because they serve as an indicator of venture quality when other high-quality signals are unavailable.[16]

In columns (3) and (4), we control for information availability and quality of each focal venture's connected firms. In this case, the dummy variable $High\ WPIC\ (connected\ ventures)$ indicates

Table 2.5
Venture team network and market-to-book

This table reports estimation results from regressions of venture market-to-book value on team centrality, and control variables. Market-to-book is defined as the unitary token price multiplied by the circulating token supply relative to the funding amount collected via the token offering. Team centrality is expressed as the aggregated monthly normalized PCA centrality over all team members included in the *ICObench* database and trading on *Coinmarketcap* between October 2017 to July 2019. Column (1) estimates the first-stage Heckman correction model (see Equation 2.7). Model (2) applies team centrality as explanatory variable. Column (3) adds further controls for characteristics following existing IPO and token offering literature. Column (4) shows the results of the Inverse Mills Ratio (IMR) approach. Column (5) uses the generalized residuals (see Equation 2.10) as an instrumental variable (IV) for high team centrality. Model (6) - (9) follow the same approach exchanging team centrality for a dummy variable indicating whether venture i exhibits above median team centrality or not. To avoid simultaneity, we regress contemporaneous values of the dependent variables on one-month lagged explanatory variables in all our regression analyses. All specifications include country and month-year fixed effects. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For a detailed description of underlying data, see Table A1 in the appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model:	Selection	Main		IMR	IV	Main		IMR	IV
Dependent variable:	$1_t^{\text{High-centrality}}$	Market-to-book$_t$							
Team centrality$_{t-1}$		1.362^{***}	1.072^{***}	1.226^{***}	1.405^{**}				
		(0.400)	(0.349)	(0.360)	(0.554)				
High team centrality (dummy)$_{t-1}$						0.816^{**}	0.742^{**}	0.839^{***}	0.739^{**}
						(0.326)	(0.288)	(0.297)	(0.290)
Market characteristics:									
Volatility$_{t-1}$	0.220		3.255	3.395	3.311		3.183	3.303	3.183
	(1.379)		(3.255)	(3.252)	(3.158)		(3.243)	(3.238)	(3.124)
Bitcoin price ($k)$_{t-1}$	-0.000^{***}		0.001	0.000	0.001		0.000	0.000	0.000
	(0.000)		(0.000)	(0.001)	(0.001)		(0.001)	(0.001)	(0.000)
Human capital characteristics:									
Team size	-0.006		0.045	0.052^{*}	0.044		0.046	0.053^{*}	0.046
	(0.011)		(0.030)	(0.031)	(0.029)		(0.030)	(0.031)	(0.029)
Technical experience (dummy)	0.155^{***}		0.237^{***}	0.317^{***}	0.228^{***}		0.239^{***}	0.313^{***}	0.239^{***}
	(0.030)		(0.077)	(0.091)	(0.075)		(0.077)	(0.090)	(0.074)

(*continued*)

Table 2.5 — *continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model:	Selection	Main		IMR	IV	Main		IMR	IV
Dependent variable:	$1_t^{\text{High-centrality}}$	Market-to-book$_t$							
Industry experience (dummy)	-0.286***		-0.454***	-0.625***	-0.436***		-0.457***	-0.615***	-0.457***
	(0.026)		(0.067)	(0.118)	(0.068)		(0.067)	(0.119)	(0.064)
PhD (dummy)	-0.209		2.119***	1.935***	2.163***		2.007***	1.822***	2.006***
	(0.131)		(0.317)	(0.343)	(0.309)		(0.312)	(0.343)	(0.300)
Success index	0.264***		-0.031	0.079	-0.045		-0.020	0.083	-0.019
	(0.029)		(0.042)	(0.083)	(0.045)		(0.042)	(0.084)	(0.041)
Venture & fundraising controls	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time & country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.345	0.335	0.610	0.611	0.609	0.332	0.609	0.610	0.609
Adjusted R-squared	n/a	0.301	0.580	0.581	0.580	0.298	0.579	0.580	0.579
Observations	1,170	1,004	1,004	1,004	1,004	1,004	1,004	1,004	1,004

Table 2.6
Information availability and team centrality

This table reports estimation results from regressions of venture liquidity and market-to-book value on team centrality, moderation and control variables. All variables introduced in Table 2.4 and Table 2.5 are defined and calculated identically. Low WPIC (focal venture) is a dummy indicator that takes the value of 1 if a venture's white paper provides additional information in comparison to its industry peers' white papers below the 10^{th} percentile, and 0 otherwise. High WPIC (connected ventures) is a dummy indicator that takes the value of 1 if the average information content of white papers distributed by the focal venture's connected ventures is above the 90^{th} percentile. Control variables including the respective dummy for Low WPIC and High WPIC are suppressed for brevity. To avoid simultaneity, we regress contemporaneous values of the dependent variables on one-month lagged explanatory variables in all our regression analyses. All specifications include country and month-year fixed effects. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For a detailed description of underlying data, see Table A1 in the appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	IMR	IV	IMR	IV	IMR	IV	IMR	IV
Dependent variable:	Trading volume$_t$				Market-to-book$_t$			
High team centrality$_{t-1}$	3.487**	2.846*	5.051***	4.226**	0.582*	0.516*	0.722 **	0.600*
	(1.669)	(1.642)	(1.821)	(1.813)	(0.307)	(0.305)	(0.307)	(0.341)
High team centrality$_{t-1}$								
× Low WPIC (focal venture)	14.183**	13.676**			2.565***	2.394***		
	(5.976)	(5.711)			(0.774)	(0.715)		
× High WPIC (connected ventures)			1.998	2.400			0.597	0.640
			(3.462)	(3.389)			(0.570)	(0.556)
Market controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Human capital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Venture controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fundraising controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.428	0.426	0.425	0.424	0.622	0.621	0.613	0.612
Adjusted R-squared	0.382	0.381	0.379	0.378	0.592	0.591	0.582	0.581
Observations	1,011	1,011	1,011	1,011	1,004	1,004	1,004	1,004

that connected ventures of the focal venture publish high-quality white papers, i.e., provide relatively high levels of formal information to the market. While the estimated coefficient on the interaction term between $High\,WPIC\,(connected\,ventures)$ and $High\,team\,centrality$ is insignificant in both models, those of $High\,team\,centrality$ even increase in statistical significance. This indicates that network-based (informal) information matters also if formal information availability and quality of connected firms is high. Overall, these results confirm our general conjecture that team network connections are an important channel for the dissemination of information between ventures which is merely independent of the publicly available tangible information set about peer ventures in the market.

The additional estimation results in columns (5) to (8) using our second success measure, $Market{-}to{-}book$, exhibit similar patterns. Again, the coefficient estimates on the interaction terms between team centrality and $Low\,WPIC\,(focal\,venture)$ are statistically significant at the 1% level, while those involving the $High\,WPIC\,(connected\,ventures)$ indicator are insignificant. Taken together, the evidence corroborates Hypothesis 2, suggesting that the positive relation between team member centrality and venture success is more pronounced in the absence of tangible information in the market for token offerings.

2.5.3 Advisor team centrality and post-funding success

So far, our results provide evidence consistent with the proposition that a venture's team network is positively related with post-funding success. To supplement our main analysis, we re-estimate the models presented in Table 2.4 and Table 2.5 by adding different measures of the ventures' external advisor network centrality, namely $Advisor\,centrality$ and $High\,advisor\,centrality$, to our baseline specification. The results of this extended model are shown in Table 2.7. The estimated coefficients of $Advisor\,centrality$ and $High\,advisor\,centrality$ are statistically insignificant throughout all model specifications for both of the venture success indicators (with the exception of column (5) and the IV model in column (8)). This suggests that advisors' networks are no longer relevant for venture success after the initial funding campaign has ended. As outlined above, a potential explanation for this observation is that while team members have incentives to remain committed to further build up the venture and create long-term value, advisors' support usually ends with the token offering. In contrast, and equivalent to our baseline models, the coefficients on $Team\,centrality$ and $High\,team\,centrality$ is positive and highly statistically significant. This confirms that the documented impact of team networks on venture success remains robust after controlling for the influence of advisor networks.

These results add to current findings in Giudici et al. (2020), who document that the network position of the advisor team is relevant for ventures' initial funding success.[17] Our own analysis indicates that advisors' networks are no longer relevant for venture success after the funding campaign has ended. As explained above, a potential explanation is that while team members have incentives to remain committed to further build up the venture and create long-term value, advisors' support usually ends with the token offering.

2.6 Discussion and concluding remarks

2.6.1 Summary of main results

Our study explores the relationship between team networks, venture success, and the level of information availability in the context of young, token-financed ventures. We test the hypothesis that venture success, measured in terms of higher token trading volumes and higher market valuations, is positively related to quality signals and information benefits obtained through stronger (more central) team networks. Recognizing that early-stage ventures face a high level of uncertainty, social ties enable them to enhance communication flows and strengthen their credibility. From a theoretical perspective, we refer to these information-based effects as the *certification effect* (Cohen et al. (2008), Ozsoylev et al. (2013), Rossi et al. (2018), Maggio et al. (2019)) and the *connection premium* (Bajo et al. (2020)). High network centrality is likely to reduce asymmetric information and increase trust among the key parties involved in the token offering transaction. It further improves the management of complexity and the mobilization of resources in a venture project (Harris and Helfat (2007)). In the absence of quality signals and other tangible information, well-connected ventures have access to informal information through the network, benefit from the *connection premium* and the *certification effect*, and ultimately exhibit higher venture success.

This study is the first to document this team network-venture success relationship empirically. Our findings hold after controlling for potential reverse causality and selection concerns. The estimated effects are not only statistically significant but also economically meaningful. For example, in the hypothetical scenario in which two identical (average) ventures trade on *Coinmarketcap* with teams who only differed in their centrality by one standard deviation, the more centrally positioned

Table 2.7

Venture advisor network and post-funding success

This table reports estimation results from regressions of venture liquidity and market-to-book value on advisor centrality, and control variables. All variables introduced in Table 2.4 and Table 2.5 are defined and calculated identically. To avoid simultaneity, we regress contemporaneous values of the dependent variables on one-month lagged explanatory variables in all our regression analyses. All specifications include country and month-year fixed effects. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For a detailed description of underlying data, see Table A1 in the appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Trading volume$_t$				Market-to-book$_t$			
Advisor centrality$_{t-1}$	-2.278	-4.118			-1.687***	0.258		
	(2.180)	(2.938)			(0.496)	(0.500)		
Team centrality$_{t-1}$	4.917***	5.429***			1.842***	1.216***		
	(1.846)	(1.999)			(0.397)	(0.361)		
High advisor centrality (dummy)$_{t-1}$			0.323	4.421			-0.641	2.597***
			(1.813)	(3.010)			(0.393)	(0.503)
High team centrality (dummy)$_{t-1}$			3.763**	4.491***			1.068***	0.553*
			(1.610)	(1.693)			(0.355)	(0.301)
Market characteristics:								
Volatility$_{t-1}$		14.465		14.427		3.542		3.055
		(21.383)		(20.600)		(3.219)		(3.172)
Price (log)$_{t-1}$		13.254***		14.226***				
		(1.804)		(1.767)				
Bitcoin price ($k)$_{t-1}$		14.816***		14.297***		0.674		0.398
		(2.851)		(2.805)		(0.495)		(0.498)
Human capital characteristics:								
Team size		0.030		0.045		0.061*		0.071**
		(0.170)		(0.166)		(0.032)		(0.034)
Advisor size		-0.468		-1.075***		-0.149***		-0.343***
		(0.295)		(0.358)		(0.053)		(0.068)
Technical experience (dummy)		1.070**		0.736		0.206***		0.104
		(0.449)		(0.448)		(0.079)		(0.079)

(*continued*)

Table 2.7 — *continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Trading volume$_t$				Market-to-book$_t$			
Industry experience (dummy)		-1.069***		-0.968***		-0.474***		-0.454***
		(0.345)		(0.344)		(0.066)		(0.064)
PhD (dummy)		5.541***		5.495***		2.152***		2.222***
		(1.863)		(1.855)		(0.318)		(0.304)
Success index		-0.346		-0.391		-0.020		-0.041
		(0.301)		(0.289)		(0.044)		(0.043)
Venture & fundraising controls	No	Yes	No	Yes	No	Yes	No	Yes
Time & country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.309	0.424	0.310	0.428	0.345	0.613	0.334	0.623
Adjusted R-squared	0.273	0.379	0.274	0.382	0.311	0.583	0.299	0.593
Observations	1,011	1,011	1,011	1,011	1,004	1,004	1,004	1,004

venture would increase its trading volume by $2.1 million per month, and its market-to-book value would rise by 11.9%. On the one hand, strong team ties with other ventures and a higher network centrality position ventures at the crossroads of information flow. On the other hand, a venture's central position in the overall network facilitates reaching a more visible and prominent position compared to other, more peripheral ventures. Our empirical results underline that both channels help to explain the team network-venture success relationship.

2.6.2 Theoretical contributions and practical implications

Our study makes several important theoretical contributions to the literature. We highlight the importance of including network structures when examining information flows and success factors of entrepreneurial ventures. In the prior literature, the funding and post-funding success implications of entrepreneurial networks have received little attention. To the best of our knowledge, existing evidence is limited to Giudici et al. (2020), who show how the network of the advisory board affects initial funding success but neglect the impact of social networks at the ventures' operational level, i.e., how team networks affect venture success. Beyond their analysis, the social network attributes of startup teams have remained a blind spot in entrepreneurship literature. Our study closes this research gap and further adds valuable insights to the growing strand of literature that examines the effects of human capital characteristics and intra-firm connections in entrepreneurial settings (An et al. (2019), Perez et al. (2020), Momtaz (2021a), Lyandres et al. (2022)).

While we limit our analysis to a sample of token-financed ventures for empirical and economic reasons, we believe that the implications of our analyses have external validity and are also of significant practical importance for conventional startups as well as the entrepreneurial ecosystem. Our research indicates that professional networks may play a crucial role in improving venture performance in two different ways: certifying quality and facilitating information flows. Entrepreneurial teams should consider leveraging their professional ties to obtain necessary operational information input in order to build successful firms. Moreover, as ventures and networks develop, connecting with other highly central players may provide symbolic benefits to outside stakeholders. Building and maintaining ties of trust and knowledge can help new ventures to manage unknowns and gain operational advantages over more peripheral competitors, thereby ensuring long-term success.

2.6.3 Limitations and avenues for further research

Our study is the first to explore the role of team network structures in the context of early-stage venture success. The documented findings can be viewed as initial empirical evidence which provides a starting point for future research on venture team networks. To further enhance the understanding of the relationship between network structures and venture success, we encourage future research to extend our empirical analysis to the context of VC-financed startups and the financial performance effects of well-connected teams. Thereby, financial performance may refer to the probability of a successful exit or IPO as well as short-term and long-run capital market effects. Additionally, it seems straightforward to also focus on the impact of team networks on non-financial outcome variables.

While we focus on a general definition of network ties, it might further be insightful to extend our analysis to sub-networks with specific characteristics, e.g., industry networks. It seems reasonable to assume that these sub-networks better reflect the flow of specific information and help to better understand how network-based information shapes entrepreneurial decision making.

In general, we hope to pave the way for future research on team networks in entrepreneurial finance. Our study serves as an invitation for entrepreneurship scholars to further investigate the role of team networks in a broader and more extensive setting which goes beyond the empirical framework of this study.

Endnotes

[1] We use the terms (network) centrality and connectedness interchangeably.

[2] Token offerings have emerged as a new attractive form of financing firms from small startups to large multinational corporations. However, as mostly performed by businesses in their first stages of operations, we use “venture” or “startup” as the uniform term to describe businesses, who carried out a token offering.

[3] In our study, we relate to social networks as determining the social capital of firms. Social capital is a multi-faceted construct and implies various dimensions, levels, types, and determinants (Coleman (1988), Putnam et al. (1992)). Lacking a single definition, the commonality of most definitions emphasizes the role of social relations in generating productive benefits for individuals and society as a whole.

[4] We use project, startup, and venture interchangeably throughout the paper.

[5] Momtaz (2019, p. 6–8) provides a detailed comparison of token offerings to conventional financing methods.

[6] We use aftermarket, secondary market, and post-funding phase interchangeably.

[7] Within our sample, we find that venture advisors participate in 5.074 projects, on average, while the average team member is involved in 1.276 ventures.

[8] While our sample and centrality measures deviate from Giudici et al. (2020), we are able to replicate their finding that advisor centrality is positively and significantly correlated with fundraising success. Moreover, we find that team centrality is another key factor to maximize the funding success of token-financed ventures which goes beyond the impact of advisor networks. These results are not tabulated, but available upon request.

[9] For an extensive overview of available token offering databases refer to Lyandres et al. (2022).

[10] As of March 2023, *ICObench* data is no longer available for download. A viable alternative for future studies is the Token Offerings Research Database (TORD), which is freely available for download from `www.paulmomtaz.com/data/tord`.

[11] Terms potentially referring to causality, e.g., “explain”, “outcome” or “predictor”, are used in a general statistical sense to designate variables in a model and observed empirical relationships.

[12] Larcker et al. (2013) point out one problematic feature of aggregated centrality measures: as larger firms tend to have larger boards, which is also applicable to our case of the overall venture team, firm size and connectedness are mechanically positively associated. Based on their concern that created networks rather serve as imperfect proxies for firm size, they sort firms into size (log of market capitalization) quintiles and rank them within each size quintile based on their centrality. In untabulated results, we test the average monthly Pearson correlations between each centrality measure with size (log of market capitalization). Based on the low correlations ranging from 23% to 5%, we consider the potential impact of the positive mechanical association of team or advisor centrality and venture size as low. Although we refrain from ranking venture size and centrality measures, we respectively control for venture team and advisor size in our main analyses.

[13] Florysiak and Schandlbauer (2022) show that lower informative content, i.e., less additional disclosure of information beyond what is already contained in white papers of peer ventures, leads to higher information asymmetry between investors and the token issuing venture.

[14] Our measures of centrality could be correlated with some unobserved or omitted venture characteristic that is associated with success. For example, higher quality members may be more likely to engage in better connected venture teams, i.e., there is a matching between high quality team members and well-connected (or more prestigious) ventures. Similarly, better connected team members may prefer to participate in projects they correctly anticipate to perform well in the future.

[15] Using the lower bound of the estimated coefficients, the computation is as follows: $(0.739 \times 0.425)/5.022 = 6.3\%$, where 5.022 is the sample mean of $Market{-}to{-}book$.

[16] To explore the robustness of our results, we consider an alternative threshold for $Low\,WPIC\,(focal\ venture)$, which takes the value of 1 if the focal white papers' information content falls below the 20$^{\text{th}}$ percentile, and 0 otherwise. In results not shown, we obtain similar coefficients, both in terms of magnitude and significance.

[17] In results not shown, we are able to confirm in our data set that both $Advisor\ centrality$ and $Team\ centrality$ are positively and significantly related to funding success.

Appendix

See next page for Table A1.

Table A1
Definition of control variables

This appendix provides definitions and data sources for the main control variables used in the study.

Variable	Definition	Source
Venture characteristics		
Blockchain (dummy)	A dummy variable indicating whether the tokens are created using the Ethereum blockchain, which represents the technical standard for the creation of fungible tokens.	ICObench
Open source (dummy)	A dummy variable indicating whether the venture discloses its source code on GitHub.	GitHub
Industries	The number of distinct industries targeted by the venture's token offering. Serves as a proxy for diversification.	ICObench
Size	The natural logarithm of one plus the total amount raised in the token offering (converted to $m, including pre-sale).	As above
Market characteristics		
Volatility	The average monthly standard deviation of the token price on Coinmarketcap.	Coinmarketcap
Price (log)	The natural logarithm of one plus the monthly average token price on Coinmarketcap.	As above
Bitcoin price ($k)	The monthly average of the Bitcoin price in $k on Coinmarketcap.	As above
Human capital characteristics		
Team size	The number of team members excluding advisors at the start of the token offering.	ICObench
Advisor size	The number of advisors at the start of the token offering.	As above
Technical experience	The number of team members with a university degree in a technological field (e.g., engineering, information technology).	As above
PhD (dummy)	A dummy variable indicating whether at least one team member holds a PhD.	As above
Industry experience	The number of team members with prior experience in the blockchain industry.	As above
Success index	The number of team members which participated in a successful token offering prior to the present token offering.	As above
Fundraising characteristics		
Token supply	Total amount of tokens that can be issued according to the token offering's smart contract.	ICObench
Competition	The number of token offerings starting in the same month.	As above
Duration (days)	The length of the token offering in days (excluding pre-sale phase).	As above
Platform (dummy)	A dummy variable indicating if the token offering relies on the technical standard ERC20.	As above
Airdrop (dummy)	A dummy variable indicating free tokens were distributed in exchange to, for example, promoting the venture via social media.	As above
Pre-sale (dummy)	A dummy variable indicating if the venture attempted a pre-sale event prior to the token offering (irrespective if successful or not).	As above

(*continued*)

Table A1 — *continued*

Variable	Definition	Source
Bonus program (dummy)	A dummy variable for whether the venture offered a bonus program in a token offering. A bonus program typically offers discounted or free tokens as soon as a minimum predetermined investment amount is received from individual wallet addresses.	As above
KYC process (dummy)	A dummy variable for whether the token offering complies with the "know your customer" requirement.	As above
Investor registration (dummy)	A dummy variable for whether the token offering offers a whitelist to early investors.	As above
Hardcap (dummy)	A dummy variable for whether the venture has announced a hard cap for the token offering A hard cap represents the maximum funding amount that the venture accepts. As soon as it is reached, the token offering ends, and excess funding collected is returned to investors.	As above
Softcap (dummy)	A dummy variable for whether the venture has announced a soft cap for the token offering. A soft cap represents the minimum funding amount at which the venture's collection of funds is deemed successful. Token offerings that fail to reach the soft cap usually redeem the full funding amount to investors.	As above
Video (dummy)	A dummy variable for whether the venture created a video to promote the token offering.	As above
Low WPIC (focal venture)	A dummy variable that takes the value of 1 if a venture's white paper provides additional information in comparison to its industry peers' white papers below the 10th percentile, and 0 otherwise.	Authors' own calculations based on Florysiak and Schandlbauer (2022)
High WPIC (connected ventures)	A dummy variable that takes the value of 1 if the average information content of white papers distributed by the focal venture's connected ventures is above the 90th percentile.	As above

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CHAPTER 3

Venture Capital Investor Heterogeneity and Funding Success

Abstract

This study examines the relationship between investor heterogeneity and VC funding success. Specifically, we analyse how heterogeneity among VC investors affects the post-seed funding success of startups. Our results indicate that cultural disparities among individual investors significantly decrease the probability of obtaining VC funding in subsequent rounds, and also negatively impact the amount of future VC funding raised. Our results remain robust to alternative measures of investor heterogeneity and controls for endogeneity concerns common to entrepreneurial finance studies. Our sample consists of nearly 19,000 US-based startups seeking VC funding from 2010 to 2022. Overall, our analysis deepens our understanding of how diverse ownership affects firm success in the entrepreneurial context.

3.1 Introduction

In recent years, there has been considerable interest in diversity from policy-makers, regulators, investors, corporations, and academics. The call for greater diversity, particularly in the boardrooms of established corporations, has led researchers in various fields to examine the implications of different aspects of heterogeneity[1] on decision making and firm-level outcomes. These include gender diversity (Campbell and Mínguez-Vera (2008), Carter et al. (2010), Báez et al. (2018)), ancestral diversity (Giannetti and Zhao (2019), Barg et al. (2023)), cultural diversity (Ahern and Dittmar (2012), Frijns et al. (2016)) and various other aspects of heterogeneity, such as education, experience, and tenure. In accordance with the extensive research on diversity in publicly listed firms, entrepreneurship research provides mixed results on the performance implications of the extent of diversity in founding teams (for a review see Huang et al. (2023)).

Although previous diversity literature has primarily focused on boards and teams, a growing body of research is now investigating the heterogeneity implications from the investor perspective (Ng et al. (2015), Huang and Petkevich (2016), Kim et al. (2021)). Nonetheless, prior empirical evidence on the relationship between investor heterogeneity and future performance is inconclusive and limited to the context of established corporations.

Given that early-stage firms face severe difficulties to attract traditional debt financing and have a high need for financial resources to grow, venture capital investors (VCs) represent a fundamental financial, but also know-how, expertise, and networking resource for young, innovative firms (Hellmann and Puri (2002), Colombo and Grilli (2010)). Unlike traditional passive investors such as banks, VCs are typically institutional investors or wealthy individuals that are actively involved in building and managing their portfolio companies. They invest in a range of different stages of a startup's development, from seed funding to bridge investments, and often syndicate their investments with other VCs (Lerner (1994), Tian (2011), Dai and Nahata (2016)). With cross-border investments becoming increasingly common in the VC market, there is a large potential for diversity and complementary among a startups' group of investors, inducing interdependence and mutual exchange requirements (Ferrary (2010)), but simultaneously a higher variety of experience, expertise, incentives, networks, and perspectives (Anderson et al. (2011)).

While the interest in geographical and cultural similarity between VCs and their investees (e.g., Cumming et al. (2009), Devigne et al. (2013), Humphery-Jenner and Suchard (2013), Bertoni and Groh (2014), Li et al. (2014), Cumming et al. (2016), Chahine et al. (2019)) has grown in recent years, researchers have paid limited attention to the impact investors with multi-dimensional cultural or local backgrounds may have on the growth of their portfolio firms. Since each investor contributes distinct insights and divergent thinking to foster sustainable growth and value for his investments, the concept of investor heterogeneity may be an important aspect of entrepreneurial success. Building on the mixed evidence that institutional, geographical, and cultural distance between ventures and lead investors have an impact on VC-invested firm outcomes, the main challenges VCs and their portfolio firms face may not only arise from physical distance (Li et al. (2014), Dai and Nahata (2016), Khurshed et al. (2020)). Since it is not entirely clear whether cultural heterogeneity among early-stage investors, representing one form of ownership-related diversity, matters, this study aims to better understand the effects of investor heterogeneity on entrepreneurial venture outcomes.

Using data on funding rounds of US-based startups between 2010 and 2022 from Crunchbase, we are able to trace the local and cultural origin of involved VCs. Based on our measure of cultural investor heterogeneity using Hofstede's cultural dimensions, we find a negative and statistically significant impact of investor heterogeneity on funding success. The findings remain robust after controlling for selection bias through a Heckman selection correction and an adjusted instrumental variables approach as well as investor and firm characteristics known to affect VC funding success. Furthermore, our results continue to hold after considering funding size as an alternative dependent variable and alternative proxies for investor heterogeneity.

Our paper contributes to the existing literature in the following ways. First, we provide new evidence on the impact of investor-related diversity and firm success. Second, we contribute to the growing literature on cultural distance and the success of VC-financed startups by investigating the impact of cultural distance on investment decisions. In particular, our evidence underscores the potential drawbacks of cultural heterogeneity by showing that receiving funds from culturally more distant VCs has a negative effect on startup growth.

3.2 Theory and hypotheses

VCs target very specific kinds of investments. They look for newly established enterprises that represent a potentially high-growth business and therefore require larger funding. Organizationally, a VC firm is a pool of capital organized as a limited partnership. From there, investments are made in nonpublic companies that represent an opportunity to generate high rates of return within 5 to 7 years (Gompers and Lerner (2004)). Generally, VCs may invest throughout different stages of a company's life cycle. The different stages range from the "seed stage" and "early stage", where no real product or company is organized yet, to the "expansion stage" and "bridge stage". Throughout these later stages, the business grows further through market extension and product diversification. Additional serial funding is typically obtained to support expansion and exit activities such as an acquisition or IPO. As Gompers (1995) mentions, VCs are understood to provide intensive monitoring and coaching of their portfolio firms. The VCs' commitment includes frequent informal visits, meetings with customers and suppliers, and board positions with active involvement in major strategic and personnel decisions.

A typical and enduring characteristic of the VC industry are syndicated investments. Tian (2011), for example, finds that three-quarters of all US startups are backed by multiple VCs. This relates to the fact that the VC market itself is prone to extensive information asymmetries, incentive problems but simultaneously high growth potential (Amit et al. (1998), Gompers and Lerner (2001), Tykvová (2007)). As VCs can share the risk and transaction costs related to startup financing via syndication, the rationales, structures and performance implications of syndicated investments have been extensively studied in extant literature (Lerner (1994), Tian (2011), Nahata et al. (2014)).[2] While especially in the earlier stages of the VC industry, geographical proximity was deemed necessary to reduce information asymmetries and related adverse selection and moral hazard problems (Cumming and Dai (2010)), syndicates commonly draw investors from different nations. This is driven by enhanced domestic competition in mature VC industries, which has highly increased cross-border VC transactions since the early 1990s (Schertler and Tykvová (2011), Chemmanur et al. (2016)).

A large body of literature examines the country-level and firm-level determinants of international VC, its strategies and its economic outcomes.[3] Research on international VCs has documented that private firm success is impacted differently by syndicates comprising both domestic and cross-border VCs. From the perspective of portfolio companies, several studies show that international VCs help their investees to grow in terms of sales, assets and employment, and expand to cross-border and public capital markets (Cumming et al. (2009), Devigne et al. (2013), Cumming et al. (2016), Chahine et al. (2019)). However, studies on VC investor success present mixed evidence on the most important step in the VC cycle, the investors' exit. On the one hand, prior work suggests that the probability and value of an acquisition or IPO is higher for international VCs (Bertoni and Groh (2014), Cumming et al. (2016), Chahine et al. (2019)). On the other hand, some studies find that purely domestic VCs are more likely to exit their investments successfully than foreign-backed ventures (Humphery-Jenner and Suchard (2013), Li et al. (2014)).

While international syndication has advantages, investing in and with less familiar foreign countries may significantly impact the relationships between investors and investees alike. Prior empirical evidence shows that cultural distance between VCs and the portfolio firm negatively affects VC performance in three related ways. We argue, that similar conclusions can be drawn as we investigate cultural heterogeneity within the respective investor group.

The first factor relates to hindered communication effectiveness. Amit et al. (1998) and Dai et al. (2012) emphasize informational issues between VCs and their investees. According to Thomas and Peterson (2016), cross-cultural management theory explains that effective communication between two parties might be hindered by, for example, fundamentally different communication patterns (e.g., communication in low power distance cultures flows more diffused and less along hierarchical channels as opposed to high power distance cultures), attention patterns (e.g., more versus less attention to more powerful and authorities) and communication styles in general (e.g., more explicit communication in individualistic societies versus implicit communication in collectivist societies).

Second, cultural differences indicate dissimilarity in essential values and beliefs. Regarding the VC-investee relationship, such dissimilarity raises barriers to information sharing, reduces trust, increases transaction costs and, ultimately, the potential for conflict (Dai et al. (2012), Li et al. (2014), Nahata et al. (2014), Dai and Nahata (2016)). For instance, VCs in the US regularly seek direct confrontation with the CEOs of their portfolio companies (Fried and Hisrich (1995)); in China, however, direct confrontation is detrimental for interpersonal relationships as advice is usually provided in an indirect and "face saving" manner (Ahlstrom and Bruton (2006)). Thus, VCs may drift apart in their expectations on how, for example, governance structures and measures shall be implemented in their common portfolio company. Investors with high uncertainty avoidance may prefer to establish a highly formalized and hierarchical corporate governance system to reduce uncertainty. However, investors with less uncertainty avoidance may propose flexible structures to leave room for improvisation and innovation (Hofstede (2001), Li et al. (2014)). In this case, highly divergent investors are unlikely to agree upon and maintain an ideal and well-functioning governance model for all parties, including the venture itself, involved.

Third, extant literature illustrates the "liability of outsidership" (Johanson and Vahlne (2009), Vaara et al. (2012)), suggesting that cultural differences manifest in the level of confidence in each other and increased social discrimination, which ultimately leads to poorer VC performance. Sociological theory notes that homophily, one of the most powerful sociological mechanisms to influence the formation of relationships, implies that similarity leads to attraction and trust, while people refrain from forming relationships with individuals of different values and beliefs (Sorenson and Stuart (2001), Vaara et al. (2012)). Given that trust builds the foundation for a healthy climate of exchange of ideas and information sharing between VCs, cultural heterogeneity might hinder the transfer of knowledge that is required for business building, monitoring and an efficient allocation of resources (Park et al. (2012)).

In summary, existing research on cultural distance implies that heterogeneous investors are characterized by different values, beliefs and practices. Given the important role of VCs in providing capital to young and high-risk companies that face severe difficulties to attract external financing, we expect that, other things being equal, ventures with a highly culturally heterogeneous investor base are less likely to succeed in future funding rounds.

We thus hypothesize that cultural distances will have a negative impact on the likelihood of successful VC funding. In accordance with the arguments illustrated above, we derive:

Hypothesis (H1): *The heterogeneity of venture capital investors has a negative impact on the probability of successful future funding rounds.*

Hypothesis (H2): *The heterogeneity of venture capital investors has a negative impact on the amount of funds raised in future funding rounds.*

3.3 Data and methodology

3.3.1 Sample

The primary database used in this paper is Crunchbase (`www.crunchbase.com`), an in entrepreneurship research widely used provider of data on VC investments (see, e.g., Ter Wal et al. (2016), Butticè et al. (2022), Guzman and Li (2023), Seigner et al. (2023)).[4] Crunchbase is a crowd-sourced data platform performing particularly well in covering innovative startups that collect funding from institutional investors (Guzman and Li (2023)). The data include information on ventures, their teams, financing rounds and the respective investors. Since both active and deceased firms are made obtainable, the present analysis includes ventures of any status and is not subject to survivorship bias.

As we focus on VC investments in the US, our final sample comprises 31,325 firm-funding series observations of 19,141 distinct ventures that sought VC funding between 2010 and 2022. It consists of 204,918 investments made by 17,223 individual investors throughout seed and post-seed funding rounds. A breakdown of the sample by investor country is provided in Table 3.1.

Given that VC as an organized system has its origin in the US, it is not surprising that according to the statistics shown in Table 3.1, 85.76% of investments in US ventures are made by US investors. This is followed at great distance by investors from the UK (1.97%), which is characterized by an active capital market and a positive attitude towards risk-taking (Ooghe et al. (1989)). Moreover, 1.20% of our sample investments originate from China, which according to Chen (2022) has become the second largest VC market in the world. Notably, VCs originate from the US in 63.69% of our sample cases. Foreign VCs are widely dispersed around the globe and are based in, for example, China (3.19%), Japan (2.19%) or Israel (1.53%).

Table 3.1
Country-wise distribution of VCs

This table depicts the number and percentage share of venture capital investors in the Crunchbase sample by country of origin between 2010 and 2022 as well as the number of funding round participations by these investor countries. In general, one funding round may consist of several investments by different investors.

Country	Funding rounds (N)	Funding rounds (%)	Investors (N)	Investors (%)
United States	175,735	85.758	10,976	63.691
United Kingdom	4,036	1.969	737	4.276
China	2,454	1.197	550	3.191
Canada	2,073	1.011	475	2.756
Israel	1,952	0.952	264	1.531
Germany	1,715	0.836	330	1.914
Japan	1,640	0.800	378	2.193
Singapore	1,359	0.663	220	1.276
France	1,327	0.647	242	1.404
Switzerland	1,110	0.541	181	1.050
Hong Kong	921	0.449	175	1.015
Brazil	875	0.427	103	0.597
Korea	854	0.416	221	1.282
Australia	798	0.389	226	1.311
India	708	0.345	259	1.502
Netherlands	583	0.284	142	0.824
United Arab Emirates	461	0.224	85	0.493
Spain	390	0.190	104	0.603
Belgium	360	0.175	62	0.359
Taiwan	342	0.166	73	0.423
Others	5,225	2.549	1,430	8.298
Total	204,918	100%	17,223	100%

3.3.2 Econometric approach

To test our hypotheses, suggesting that higher levels of investor heterogeneity are negatively associated with venture funding success, we estimate several specifications of the following regression:

$$DV_{it} = \beta Investor\ heterogeneity_{it-1} + \gamma\Omega_{it-1} + FEs + \varepsilon_{it}, \tag{3.1}$$

where DV_{it} refers to each of our outcome variables of interest; $Investor\ heterogeneity_{it-1}$ is the respective investor heterogeneity measure over all currently invested investors in venture i in series $t-1$; and Ω_{it-1} is a vector of control variables, which is related to firm and investor characteristics.

In a first step, we examine how the likelihood of venture funding success ($Successful\ series\ A-D+$) responds to variations in investor heterogeneity ($Investor\ heterogeneity_{it-1}$). In a second step, we relate our investor heterogeneity measure to the amount of financing raised in each funding series ($Log\ series\ A-D+$). In further robustness tests, we analyse the impact of the individual components of our investor heterogeneity measure and other alternative heterogeneity measures on venture funding success and funding amount.

FEs are year-state fixed effects and city fixed effects. We introduce these FEs throughout our analyses to control for cycle-related effects and geographical variation in the VC market. All reported standard errors are robust.

As in related entrepreneurial finance studies (Colombo and Grilli (2010), Bertoni et al. (2011), Sun et al. (2020), Mansouri and Momtaz (2022)), endogeneity is a concern to our empirical framework. We are interested in the treatment effect of investor heterogeneity on ventures' funding performance. To address the econometric issue of reverse causality, i.e., that lower quality ventures attract funding from (culturally) distant VCs, we avoid simultaneity by regressing contemporaneous values of DV on one-series lagged values of $Investor\ heterogeneity_{it-1}$ and our set of control variables (Ω_{it-1}; see Equation 3.1).

To mitigate remaining doubts about violations of the exogeneity condition (i.e., $E[\Omega_{it-1}, \varepsilon_i] \neq 0$), we address sample selection bias by controlling for selection based on observed and unobserved heterogeneity.[5] Both techniques require a selection model. Therefore, we sort all values of $Investor\ heterogeneity_{it-1}$ in our sample by funding series and year to distinguish between ventures with less versus highly heterogeneous investors based on the median, resulting in a $High\ heterogeneity_{it}$ dummy variable. We model the probability that the venture i belongs to the subsample of highly heterogeneous investors in series t by using a probit model. The independent variables in this model are captured by a vector of firm and investor characteristics, denoted by $\Omega^{(s)}_{it-1}$. Formally, we estimate the following first-stage probit model:

$$High\ heterogeneity_{it} = \delta\Omega^{(s)}_{it-1} + \xi_{it} \tag{3.2}$$

Based on these estimates and following the entrepreneurial finance literature (Colombo and Grilli (2010), Sun et al. (2020), Mansouri and Momtaz (2022)), we adapt a classical Heckman correction model (Heckman (1979)) to address sample selection bias. We obtain the predicted individual probabilities from Equation 3.2 and compute inverse Mills ratios (IMRs) for the selection of ventures into a highly heterogeneous investor structure:

$$IMR_{it} = \frac{\phi(\frac{\delta\Omega_{it}^{(s)}}{\sigma_{\xi_{it}}})}{\Phi(\frac{\delta\Omega_{it}^{(s)}}{\sigma_{\xi_{it}}})}, \tag{3.3}$$

where IMR_{it} is the IMR of venture i in series t; and $\phi(.)$ and $\Phi(.)$ are the probability density and the cumulative density of the standard normal distribution, respectively. Next, we insert this ratio as an additional explanatory variable into the baseline model in Equation 3.1 to partial out a possible selection effect. Formally, we estimate:

$$DV_{it}^{IMR} = \beta Investor\ heterogeneity_{it-1} + \lambda IMR_{it-1} + \gamma\Omega_{it-1} + FEs + \upsilon_{it}, \tag{3.4}$$

As an alternative second-stage approach for the "selection on unobservables" we use an adjusted instrumental variables approach. Consistent with Gourieroux et al. (1987), Colombo and Grilli (2005), and Mansouri and Momtaz (2022), we obtain the generalized residuals (GRs) from Equation 3.2 and use them to instrument investors' heterogeneity in our baseline regression in Equation 3.1. Formally, we define the GR as:

$$GR_{it} = High\, heterog._{it} \times \frac{\phi(-\delta\Omega_{it}^{(s)})}{1-\Phi(-\delta\Omega_{it}^{(s)})} + (1 - High\, heterog._{it}) \times \frac{-\phi(\delta\Omega_{it}^{(s)})}{\Phi(-\delta\Omega_{it}^{(s)})}, \tag{3.5}$$

where GR_{it} are the GRs of venture i at time t.

3.3.3 Dependent variable

Our dependent variable of interest is funding success after ventures' initial early-stage financing, commonly referred to as seed financing. This includes funding series, usually sequentially labeled as series A, B, C and so on, where startups raise money to finance their development but also their exit efforts. First, we define successful funding (denoted $Successful\ series\ A-D+$) as a dummy variable that takes the value of 1 if the venture received VC funding in a respective funding series. As a second dependent variable, we use the amount of funds (denoted $Series\ A-D+\ financing\,(million\,\$)$) to numerically represent funding success. To avoid distribution skewness, we follow prior literature (Block and Sandner (2009), Alexy et al. (2012)) and apply the natural logarithm plus one of financial funding received in our regression models (denoted $Log\ series\ A-D+$).

We consider the success and amount of investments by various types of series financing rounds for several reasons. A large number of recent studies have adopted these measures of entrepreneurial funding success (e.g., Block and Sandner (2009), Alexy et al. (2012), Guzman and Li (2023)). Since received funding reflects realized instead of intended investments, this variable proxies for firm value at the time when investors jointly equip the startup with VC money (Alexy et al. (2012)). Furthermore, we consider the amount of required funding as highly individual and dependent on the distinctive industry and life cycle stage of each startup.

3.3.4 Measures of investor heterogeneity

We are interested in measuring the impact of investor heterogeneity on subsequent funding success and size. Following this objective, we construct heterogeneity measures that capture the extent to which US-based startups depend on an harmonious investor structure. To account for different aspects of heterogeneity, we construct five different measures from investors' origin information.

3.3.4.1 Cultural heterogeneity

First, we construct two similar multidimensional indices reflecting investors' cultural heterogeneity. Depending on the dominant theoretical perspective and methodological approach taken, culture has been defined in hundreds of ways. Despite certain criticism on the cultural dimensions and the application of "cultural distance" (see, e.g., Shenkar et al. (2008)), Hofstede's six-dimension model, which allows international comparison between cultures, is probably the most applied sociological cross-cultural framework to understand international business, management, and organizational development (see Kirkman et al. (2006)). For these reasons, and following prior studies showing that cultural differences affect the ways people act and interact significantly (Reus and Lamont (2009)), we resort to the Hofstede framework and obtain data on cultural dimensions from Geert Hofstede's website (`www.geerthofstede.nl`).

For our first and primary index of cultural heterogeneity (denoted $Cultural\,heterogeneity$), we use the full spectrum of Hofstede's dimensions of culture. As Hofstede (1980) illustrates, cultures evolve under the influence of a variety of factors such as history, the climate and economic development. The framework is built upon the primary dimensions small versus large power distance, uncertainty avoidance, individualism versus collectivism, masculinity versus femininity, long-term versus short-term orientation and indulgence versus restraint. For each dimension, we compute the cultural distance between the countries of respective VCs as the average Euclidean distance. To obtain this measure, we provide each investor with the levels of Hofstede's power distance, uncertainty avoidance, individualism, masculinity, long-term orientation and indulgence belonging to their respective country of origin. In line with prior studies on cultural distance (Malik and Zhao (2013), Dai and Nahata (2016), Barg et al. (2023)), we construct a composite measure as our main explanatory variable instead of relying on individual cultural dimensions only. Specifically,

$$Cultural\,heterogeneity = \frac{\sqrt{\sum_{i=1}^{6}(C_{d,i} - C_{d,j})^2}}{6}, \tag{3.6}$$

where $C_{d,i}$ and $C_{d,j}$ are the investor i's and j's scores on cultural dimension d. We then determine overall $Cultural\,heterogeneity$ as the average of all pairwise cultural distances between a venture's investors.

For further robustness checks (see Section 3.4.4.3), we follow Dai and Nahata (2016) and measure the composite cultural heterogeneity using the four original Hofstede measures, power distance, uncertainty avoidance, individualism and masculinity, only. We denote this as $Cultural\,heterogeneity(four\,factors)$. Moreover, we measure the cultural heterogeneity of investors with the longest tenure, i.e., the seed investors, in order to investigate how early-on investor heterogeneity (denoted $Cultural\,heterogeneity(seed\,investors)$) affects our sample ventures' success. The calculation was performed as described above using the full spectrum of Hofstede's dimensions of culture (see Equation 3.6).

3.3.4.2 Country heterogeneity

Although thoughts, beliefs, and values are shared across borders and especially between neighboring countries, our culture related index of investor heterogeneity could sometimes fail to account for the fact that national borders between two investors and recent political developments may already lead to disagreements between investors. It is therefore possible that we may observe cases with low values of $Cultural\,heterogeneity$ despite high levels of, for example, political tension. Therefore, we construct an alternative measure of investor heterogeneity, $Country\,heterogeneity$, using the Blau (1977) index, a widely used measure of heterogeneity:

$$Country\,heterogeneity = 1 - \sum_{a \in A} {P_a}^2, \tag{3.7}$$

where P_a is the percentage of a investor group's country origin a, and A is the entirety of all countries present in the investor group. The index measures the probability that two randomly selected investors from the same venture do not originate from the same country. In particular, it takes values between 0 (lower heterogeneity) and 1 (higher heterogeneity).

3.3.4.3 Geographical distance

An overarching assumption in this study is that divergent ownership involves economically costly friction. As prior research shows, non-proximity impedes communication and information flows and creates information asymmetry, which increases with distance (Coval and Moskowitz (1999), Ikovic and Weisbenner (2005), Boeh and Beamish (2012)). To determine whether the kilometer distance between VCs impacts the dynamics within commonly invested portfolio firms differently, we measure the distance between each investor pair using simple distance data between the capitals of two countries from the Center for Research and Expertise on the World Economy (`www.cepii.fr`). We then average the respective distances for each venture-series observation and construct $Geographical\,distance$.[6]

3.3.5 Control variables

Based on a careful review of extant literature, we include a wide variety of time-varying controls that may bias our estimation of funding success from investor heterogeneity. We control for a vector of firm and investor characteristics, which we denote by Ω. For brevity, we refer to detailed variable descriptions in Table B1 in the appendix.

Davila et al. (2003) and Devigne et al. (2013) outline that age effects cause differences in growth patterns. Following their approach, we include firm age, measured as the difference between the investment and the firm's founding year, as a proxy of newness. Furthermore, we control for the number of prior funding rounds and the cumulated amount of funding raised. This is important since firms with more fundraising experience are less resource-constrained. Therefore, they are likely to develop a competitive advantage over earlier stage firms. As an additional control for possible differences in funding potential, we include the cumulated number of already invested VCs prior to the respective funding round.

Obviously, there is natural heterogeneity among firms in many extraneous variables besides our controls. According to Fitzmaurice et al. (2012) and Devigne et al. (2013), constant extraneous variables (regardless of whether they have been measured or not) that may have an impact on the growth curve of ventures are not of substantive interest since the firm outcome of interest, i.e., funding success, is compared on several occasions, which eliminates their influence.

We include average investor age as our first control for investor characteristics. We measure the average age of all currently in a venture invested VCs to control for the fact that older VCs may be more experienced and are characterized by a broader network in the VC community (Sorenson and Stuart (2001)). Furthermore, we control for the average number of funding rounds conducted by all investors currently engaged in the venture, the number of portfolio firms held by those investors as well as the average number of portfolio firms successfully exited via an IPO or acquisition.

The US startup industry is dominated by large high-technological centers such as the Silicon Valley in California and the Route 128 in Boston. Based on the diverse founding and workforce conditions as well as tax and direct incentives to stimulate regional VC, we include state-year and city dummies in all our estimations.

3.4 Empirical results

3.4.1 Descriptive statistics

Before presenting the results of the multivariate analyses, we present some descriptive statistics of the main variables used in our study in Table 3.2. Notably, a detailed overview of data sources and construction principles is provided in Table B1 in the appendix.

Starting with outcomes shown in Panel A, 34.7% of all ventures in our sample receive series A financing, with an average investment of $4.42 million. The amount of collected capital rises sharply from series to series once the initial seed and series A financing were attained. In series B, for example, the average VC funding received is $16.09 million, while $40.38 million are collected in series D to F on average. However, only 47.9% of successful series A rounds are followed by successful series B rounds, while by series D, the success rate even drops to 43.8%.

Panel B of Table 3.2 reports the descriptive statistics for the investor heterogeneity measures. The average $Cultural\ heterogeneity$ for the overall sample is 2.36. For investors in the seed stage, average investor heterogeneity is 2.03, which partially relates to the fact that the investor group and therefore the potential for cultural disparity extends from funding series to funding series. The most intuitive measure to interpret, however, is $Country\ heterogeneity$. As the maximum value of 1

Table 3.2
Descriptive statistics

This table reports the descriptive statistics of the main variables used in the study. It reports the mean, median, standard deviation (SD), 25th percentile (P25), 75th percentile (P75), minimum, maximum and the number of observations (N). All continuous variables are winsorized at the first and 99th percentiles to constrain the impact of spurious outliers. Panel A reports the descriptive statistics of our dependent variables, that is series financing success and funds raised. Panel B reports the descriptive statistics of our key explanatory variables. Panels C and D report the descriptive statistics of firm characteristics and investor characteristics, respectively. The sample consists of 31,325 firm-series observations over the 2010–2022 period. For a detailed description of our definitions and data sources, see Table B1 in the appendix.

	Mean	Median	SD	P25	P75	Min	Max	N
Panel A: Dependent variables								
Successful series A	0.347	0.000	0.476	0.000	1.000	0.000	1.000	10,912
Successful series B	0.479	0.000	0.500	0.000	1.000	0.000	1.000	8,613
Successful series C	0.462	0.000	0.499	0.000	1.000	0.000	1.000	5,891
Successful series D+	0.438	0.000	0.496	0.000	1.000	0.000	1.000	5,753
Series A financing (million $)	4.415	0.000	8.649	0.000	6.762	0.000	72.000	10,912
Series B financing (million $)	16.094	0.000	27.552	0.000	22.500	0.000	149.550	8,613
Series C financing (million $)	23.612	0.000	40.654	0.000	31.600	0.000	202.500	5,891
Series D+ financing (million $)	40.376	0.000	82.000	0.000	45.000	0.000	850.000	5,753
Panel B: Investor heterogeneity measures								
Cultural heterogeneity	2.363	0.000	4.221	0.000	3.070	0.000	22.120	31,325
Cultural heterogeneity (four factors)	1.672	0.000	2.908	0.000	2.340	0.000	15.038	31,325
Cultural heterogeneity (seed investors)	2.025	0.000	4.547	0.000	0.377	0.000	22.218	17,824
Country heterogeneity	0.160	0.000	0.209	0.000	0.314	0.000	0.740	31,325
Geographical distance	2,392	1,161	2,081	1,161	3,103	500	11159	31,324
Panel C: Firm characteristics								
Firm age	4.211	4.000	3.256	2.000	6.000	0.000	22.000	31,325
Cum. funding rounds (#)	3.123	3.000	1.665	2.000	4.000	1.000	14.000	31,325
Cum. investors (#)	10.991	9.000	8.400	5.000	15.000	2.000	89.000	31,325
Cum. funding (million $)	57.305	19.100	136.621	5.250	56.000	0.025	4,112.500	31,325
Panel D: Investor characteristics								
Investor age (Ø)	15.864	13.200	10.334	8.667	20.160	2.000	65.800	31,325
Investor funding rounds (Ø)	103.594	48.375	180.708	18.714	106.462	0.000	1,402.667	31,325
Investor portfolio firms (Ø)	79.693	33.667	155.990	13.857	73.000	0.000	1,238.500	31,325
Investor exits (Ø)	0.903	0.417	1.427	0.100	1.000	0.000	9.500	31,325

would imply that all investors stem from a different country, our sample ranges from 0 (all investors of a firm stem from one country) to 0.74 (the probability that two randomly selected investors do not originate from the same country is 74%).

As to the descriptive statistics related to firm characteristics, the results in Panel C of Table 3.2 show that our sample startups on average (in the median) receive VC funding after 4.21 (4.00) years and collect $57.31 (19.10) million throughout 3.12 (3.00) funding rounds from 10.99 (9.00) investors.

Controlling for investor experience, Panel D shows that the average age of VCs is 15.86 years. The average (median) number of funding rounds of VCs in our sample accumulates to 103.59 (48.38). This involves ownership in 79.69 (33.67) portfolio companies of which in the mean less than one successful exit has been attained by an average investor.

3.4.2 Cultural heterogeneity and funding success

Our premise is that investor heterogeneity is negatively related to financing success in serial VC funding rounds. To establish a causal inference on the effect of contrasting investor cultures, we conduct different multivariate regression analyses as described in Section 3.3.2. Table 3.3 reports the results on different regression specifications, with our dummy indicator on successful funding as the dependent variable. We present the results for four different funding stages: series A, series B, series C and series D to F (denoted series D+).

To address concerns over the selection of ventures into highly heterogeneous VC ownership, we estimate the first-stage Heckman correction model (see Equation 3.2) to explain the probability that venture i belongs to the subsample of ventures with above-median investor heterogeneity in series-year t. Surprisingly, we find that, for example, a higher number of prior funding rounds in venture i decreases the probability of heterogeneous ownership. However, an on average older investor structure of venture i in $t-1$ increases the probability of a highly heterogeneous investor composition.

In our main model shown in column (2), we regress $Successful\ series\ A$ on one-series lagged, in the case of series A the seed funding stage, values of $Cultural\ heterogeneity$ and the vector of firm and investor control variables specified in Section 3.3.5. Furthermore, we add year-state and city FEs to the model to control for unobserved heterogeneity at the state and city level across time. The coefficient on $Cultural\ heterogeneity$ is negative and statistically significant at the 1% level. Supporting H1, this indicates that a highly culturally heterogeneous investor structure is associated with a lower probability of receiving series A funding after the initial seed funding.

Table 3.3
Does investor heterogeneity predict the receipt of series financing?

This table presents the estimation results for a linear probability regression of cultural investor heterogeneity and other control variables on series A, B, C and D+ funding success. Detailed variable definitions are presented in Table B1 in the appendix. Column (1) addresses the selection effect of highly heterogeneous investors (see Equation 3.2). Column (2), the main model, controls for unobserved heterogeneity at the firm level and across time and location via city and year-state fixed effects (FEs), respectively. Columns (3), (5), (7) and (9) estimate the second-stage (see Equation 3.4) Heckman correction models. Columns (4), (6), (8) and (10) use the generalized residuals (see Equation 3.5) to instrument heterogeneous ownership. We avoid simultaneity by regressing the contemporaneous dependent variables on the one-series-lagged explanatory variables in all of the analyses. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Model:	Selection	Main	IMR	IV	IMR	IV	IMR	IV	IMR	IV
Dependent variable:	$1_t^{\text{high Heter.}}$	Successful series A			Successful series B		Successful series C		Successful series D+	
Cultural heterogeneity		-0.025***	-0.024***	-0.037***	-0.066***	-0.077***	-0.048**	-0.086***	-0.056***	-0.085***
		(0.009)	(0.009)	(0.011)	(0.005)	(0.009)	(0.022)	(0.017)	(0.017)	(0.026)
Firm age (log)	0.011	-0.051***	-0.054***	-0.051***	-0.086***	-0.087***	-0.134***	-0.132***	-0.274***	-0.276***
	(0.013)	(0.007)	(0.008)	(0.006)	(0.008)	(0.007)	(0.015)	(0.014)	(0.021)	(0.023)
Cum. funding rounds (#, log)	-0.485***	-0.189***	-0.145	-0.189***	-0.021	-0.048**	0.045	0.001	0.089***	0.034*
	(0.105)	(0.030)	(0.097)	(0.029)	(0.029)	(0.021)	(0.061)	(0.024)	(0.026)	(0.020)
Cum. investors (#, log)	0.809***	0.096***	0.021	0.096***	-0.036	0.009	-0.069	0.003	-0.148***	-0.065***
	(0.037)	(0.018)	(0.166)	(0.018)	(0.052)	(0.015)	(0.116)	(0.021)	(0.045)	(0.010)
Cum. funding (million $, log)	0.104***	0.115***	0.104***	0.115***	0.057***	0.065***	0.018	0.031***	0.012*	0.019**
	(0.037)	(0.007)	(0.023)	(0.007)	(0.009)	(0.004)	(0.018)	(0.005)	(0.006)	(0.008)
Investor age (Ø, log)	0.122***	-0.038***	-0.050	-0.038***	-0.039***	-0.033***	-0.033	-0.017	-0.077***	-0.065***
	(0.023)	(0.012)	(0.034)	(0.012)	(0.012)	(0.007)	(0.026)	(0.011)	(0.014)	(0.009)
Investor funding rounds (Ø, log)	-1.526***	0.521***	0.664*	0.515***	0.414***	0.320***	0.476*	0.321***	0.207**	0.047
	(0.095)	(0.042)	(0.342)	(0.041)	(0.134)	(0.034)	(0.258)	(0.056)	(0.101)	(0.048)
Investor portfolio firms (Ø, log)	1.490***	-0.609***	-0.751**	-0.604***	-0.409***	-0.319***	-0.452*	-0.300***	-0.149	0.010
	(0.091)	(0.041)	(0.335)	(0.041)	(0.130)	(0.034)	(0.251)	(0.054)	(0.105)	(0.056)
Investor exits (Ø, log)	-0.059**	0.184***	0.192***	0.183***	0.043	0.041	-0.037*	-0.047*	-0.070**	-0.078***
	(0.029)	(0.009)	(0.018)	(0.009)	(0.027)	(0.027)	(0.021)	(0.027)	(0.030)	(0.025)
Year × state FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.153	0.174	0.166	0.196	0.168	0.211	0.199	0.249	0.201	0.231
Adjusted R-squared	n/a	0.115	0.115	0.117	0.107	0.109	0.118	0.123	0.124	0.121
Observations	29,934	10,622	10,284	10,912	8,036	8,613	5,470	5,891	5,428	5,753

Next, we estimate two second-stage selection correction models, by means of Equation 3.3 and Equation 3.5. For this, we use the individual probabilities of Equation 3.2 to obtain IMRs and calculate GRs as described in Section 3.3.2. We include the IMR in column (3). The coefficient on $Cultural\ heterogeneity$ remains highly statistically significant. The causal effect on $Successful\ series\ A$ also remains statistically significant at the 1% level as we explicitly model endogeneity in the error term in column (4) by using the GRs (see Equation 3.3) to instrument cultural heterogeneity. In line with prior applications of this approach (see, e.g., Colombo and Grilli (2010), Mansouri and Momtaz (2022)) the IV model coefficient in column (4) increases in magnitude. Overall, the results indicate that unobserved heterogeneity does not affect our inferences and cultural heterogeneity resulting from investments in a venture's seed round decreases the probability of a successful series A round.

Turning to series B, series C and series D+ success, the statistically significant coefficients in columns (5) to (10) imply that the negative association between cultural heterogeneous investors and investment round success increases with a venture i's maturity level and the related funding requirements (-0.077 in the IV model of series B (column (6)) compared with -0.085 in the IV model of series D+ (column (10))).

3.4.3 Cultural heterogeneity and funding size

In Table 3.4, we illustrate the effect of $Cultural heterogeneity$ on the amount of collected funding throughout different investment rounds. Similarly to the results outlined in Section 3.4.2, we find that $Cultural\ heterogeneity$ negatively impacts the amount of future funding raised.

While according Colombo and Grilli (2010) and other previous studies, VC financing has a dramatic positive impact on venture growth, culturally heterogeneous investors account for an estimated decrease in the amount of money raised between 5.4% (column (4)) and 35.4% (column (10)). All our coefficients on $Cultural\ heterogeneity$ exhibit high statistical significance at least at the 5% level. Moreover, the IV specification for later stage financing in series D to F (column (10)) increases the (adjusted) R^2 of the IV specification of series A (column (4)) by 0.007 (0.037). This suggests that the effect of cultural investor heterogeneity is greater in later investment rounds. Additionally, the coefficient of $Cultural\ heterogeneity$ gets larger from series to series. Overall, our results provide support for the anticipation of H2.

Table 3.4

Does investor heterogeneity predict the amount of series financing?

This table presents the estimation results for a linear regression of cultural investor heterogeneity and other control variables on series A, B, C and D+ funding amount. Detailed variable definitions are presented in Table B1 in the appendix. Column (1) addresses the selection effect of highly heterogeneous investors (see Equation 3.2). Column (2), the main model, controls for unobserved heterogeneity at the firm level and across time and location via city and year-state fixed effects (FEs), respectively. Columns (3), (5), (7) and (9) estimate the second-stage (see Equation 3.4) Heckman correction models. Columns (4), (6), (8) and (10) use the generalized residuals (see Equation 3.5) to instrument heterogeneous ownership. We avoid simultaneity by regressing the contemporaneous dependent variables on the one-series-lagged explanatory variables in all of the analyses. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Model:	Selection	Main	IMR	IV	IMR	IV	IMR	IV	IMR	IV
Dependent variable:	$1_t^{\text{high Heter.}}$	Log series A			Log series B		Log series C		Log series D+	
Cultural heterogeneity		-0.055**	-0.054**	-0.081***	-0.205***	-0.232***	-0.199***	-0.321***	-0.234***	-0.354***
		(0.022)	(0.022)	(0.025)	(0.025)	(0.040)	(0.062)	(0.062)	(0.073)	(0.121)
Firm age (log)	0.011	-0.157***	-0.164***	-0.157***	-0.309***	-0.314***	-0.521***	-0.513***	-1.198***	-1.193***
	(0.013)	(0.019)	(0.021)	(0.018)	(0.020)	(0.019)	(0.069)	(0.064)	(0.068)	(0.071)
Cum. funding rounds (#, log)	-0.485***	-0.492***	-0.379	-0.490***	-0.096	-0.198***	0.254	0.001	0.492***	0.124
	(0.105)	(0.078)	(0.232)	(0.076)	(0.128)	(0.074)	(0.266)	(0.073)	(0.113)	(0.089)
Cum. investors (#, log)	0.809***	0.207***	0.015	0.207***	-0.163	0.015	-0.437	-0.011	-0.925***	-0.332***
	(0.037)	(0.054)	(0.372)	(0.052)	(0.203)	(0.053)	(0.487)	(0.067)	(0.155)	(0.050)
Cum. funding (million \$, log)	0.104***	0.395***	0.370***	0.396***	0.430***	0.453***	0.282***	0.346***	0.337***	0.394***
	(0.037)	(0.026)	(0.049)	(0.025)	(0.035)	(0.019)	(0.076)	(0.020)	(0.034)	(0.043)
Investor age (Ø, log)	0.122***	-0.105***	-0.133*	-0.104***	-0.149***	-0.120***	-0.161	-0.082**	-0.403***	-0.318***
	(0.023)	(0.028)	(0.077)	(0.027)	(0.048)	(0.028)	(0.106)	(0.041)	(0.053)	(0.038)
Investor funding rounds (Ø, log)	-1.526***	1.399***	1.765**	1.388***	1.281**	0.916***	1.782*	0.911***	1.197***	0.056
	(0.095)	(0.117)	(0.766)	(0.118)	(0.499)	(0.136)	(1.036)	(0.191)	(0.348)	(0.221)
Investor portfolio firms (Ø, log)	1.490***	-1.600***	-1.961**	-1.589***	-1.248**	-0.895***	-1.626	-0.774***	-0.912**	0.215
	(0.091)	(0.123)	(0.756)	(0.125)	(0.485)	(0.132)	(1.001)	(0.184)	(0.369)	(0.259)
Investor exits (Ø, log)	-0.059**	0.478***	0.498***	0.475***	0.178**	0.174**	-0.191**	-0.238**	-0.331**	-0.382***
	(0.029)	(0.029)	(0.048)	(0.030)	(0.087)	(0.087)	(0.085)	(0.112)	(0.127)	(0.113)
Year × state FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.153	0.200	0.193	0.220	0.201	0.240	0.204	0.250	0.231	0.257
Adjusted R-squared	n/a	0.143	0.143	0.142	0.141	0.142	0.124	0.124	0.156	0.150
Observations	29,934	10,622	10,284	10,912	8,036	8,613	5,470	5,891	5,428	5,753

3.4.4 Robustness tests

3.4.4.1 Sensitivity analysis of baseline results

The estimated empirical models presented in Table 3.3 and Table 3.4 are very stable. Principally, the coefficients of all the investor heterogeneity and control variables remain largely unchanged across the various specifications. Still, to further test the robustness of our results, we conduct a number of additional sensitivity tests.

As a first robustness test, which we do not report to conserve space, we re-estimate our main specification (see Equation 3.1 - Equation 3.5) and mark the beginning of our sample in 2005. Furthermore, we extend our sample to international startups and also include venture rounds outside the US. All our results are similar to Table 3.3 and Table 3.4 in terms of significance and size.

3.4.4.2 Individual cultural dimensions

Our baseline specification is informative and stable. However, it is based on our choice to include all six cultural dimensions in one composite measure of investor heterogeneity. As our results may be driven by one individual cultural aspect, we disentangle the effects of a heterogeneous investor culture on funding success in Table 3.5 and Table 3.6. We find that heterogeneity in each individual cultural dimension of Hofstede has a significant negative impact on both funding success and size. Overall, the coefficient levels of heterogeneity alongside each individual cultural dimension are on a similar level.

Interestingly, the coefficients for the dimensions long-term versus short-term orientation (denoted $Cultural\, heterogeneity(long-term)$) in the respective column (4) and indulgence versus restraint (denoted $Cultural\, heterogeneity(indulgence)$) in column (6) are slightly augmented in comparison to other cultural dimensions. According to the definition for long-term versus short-term orientation, a long-term oriented society rewards diligence, thrift, and a disciplined pursuit of long-term values and achievements. This would imply, that investors with such long-term thinking project the development of a venture over many years and weigh sustainable company growth higher than, for example, quarterly results. In turn, short-term oriented cultures are proud of achieving short-term goals related to their quick response to changing circumstances. We conclude that an investor structure that drifts apart in terms of its long-term orientation entails potential conflicts of interest regarding, for instance, the development of expansion plans in a joint portfolio company.

Table 3.5
Investor heterogeneity and the probability of series financing by cultural dimension

This table re-estimates the linear probability models (see column (2) of Table 3.3) for each individual cultural dimension included within the composite measure of *Cultural heterogeneity* described in Section 3.3.2. All variables introduced in Table 3.3 are defined and calculated identically. As previously, we avoid simultaneity by regressing the contemporaneous dependent variables on the one-series-lagged explanatory variables in all of the analyses. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Successful series financing					
Cultural heterog. (power distance)	-0.020***					
	(0.005)					
Cultural heterog. (individualism)		-0.024***				
		(0.005)				
Cultural heterog. (masculinity)			-0.021***			
			(0.005)			
Cultural heterog. (long-term)				-0.024***		
				(0.003)		
Cultural heterog. (uncertainty)					-0.021***	
					(0.007)	
Cultural heterog. (indulgence)						-0.024***
						(0.003)
Firm age (log)	-0.101***	-0.101***	-0.101***	-0.101***	-0.101***	-0.101***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Cum. funding rounds (#, log)	-0.133***	-0.134***	-0.133***	-0.135***	-0.133***	-0.133***
	(0.022)	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)
Cum. investors (#, log)	0.020	0.021	0.020	0.021	0.021	0.020
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Cum. funding (million $, log)	0.058***	0.058***	0.057***	0.058***	0.058***	0.057***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Investor age (Ø, log)	-0.042***	-0.041***	-0.040***	-0.040***	-0.041***	-0.041***
	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
Investor funding rounds (Ø, log)	0.511***	0.507***	0.511***	0.505***	0.509***	0.507***
	(0.028)	(0.029)	(0.028)	(0.027)	(0.030)	(0.027)
Investor portfolio firms (Ø, log)	-0.530***	-0.526***	-0.530***	-0.525***	-0.529***	-0.526***
	(0.031)	(0.031)	(0.030)	(0.030)	(0.032)	(0.030)
Investor exits (Ø, log)	0.019	0.018	0.019	0.019	0.018	0.018
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Year × state FEs	Yes	Yes	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.135	0.135	0.135	0.135	0.135	0.135
Adjusted R-squared	0.101	0.101	0.102	0.102	0.101	0.102
Observations	31,077	31,077	31,077	31,077	31,077	31,077

Our results support our arguments on the role of cultural heterogeneity among VCs in general and of individual culture dimensions specifically. Hence, the more diverse the investor group in terms of cultural values and preferences, the lower a venture's chances of follow-on VC investments.

3.4.4.3 Alternative investor heterogeneity measures

To gain a better understanding on the impact of investor heterogeneity on VC funding success while accounting for characteristics of the firm, present investors and the respective region, we estimate

Table 3.6
Investor heterogeneity and the amount of series financing by cultural dimension

This table re-estimates the linear regression models (see column (2) of Table 3.4) for each individual cultural dimension included within the composite measure of *Cultural heterogeneity* described in Section 3.3.2. All variables introduced in Table 3.4 are defined and calculated identically. As previously, we avoid simultaneity by regressing the contemporaneous dependent variables on the one-series-lagged explanatory variables in all of the analyses. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Log series financing					
Cultural heterog. (power distance)	-0.066***					
	(0.016)					
Cultural heterog. (individualism)		-0.077***				
		(0.016)				
Cultural heterog. (masculinity)			-0.072***			
			(0.014)			
Cultural heterog. (longterm)				-0.084***		
				(0.009)		
Cultural heterog. (uncertainty)					-0.072***	
					(0.022)	
Cultural heterog. (indulgence)						-0.079***
						(0.009)
Firm age (log)	-0.329***	-0.329***	-0.328***	-0.329***	-0.328***	-0.329***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Cum. funding rounds (#, log)	-0.362***	-0.364***	-0.362***	-0.367***	-0.362***	-0.361***
	(0.067)	(0.067)	(0.067)	(0.066)	(0.067)	(0.067)
Cum. investors (#, log)	-0.014	-0.012	-0.015	-0.012	-0.013	-0.014
	(0.061)	(0.061)	(0.060)	(0.060)	(0.060)	(0.061)
Cum. funding (million $, log)	0.435***	0.435***	0.434***	0.436***	0.434***	0.434***
	(0.026)	(0.026)	(0.025)	(0.025)	(0.025)	(0.026)
Investor age (Ø, log)	-0.145***	-0.144***	-0.140***	-0.140***	-0.141***	-0.143***
	(0.022)	(0.022)	(0.021)	(0.022)	(0.021)	(0.022)
Investor funding rounds (Ø, log)	1.501***	1.489***	1.498***	1.478***	1.492***	1.488***
	(0.102)	(0.102)	(0.099)	(0.098)	(0.107)	(0.098)
Investor portfolio firms (Ø, log)	-1.503***	-1.490***	-1.501***	-1.481***	-1.494***	-1.490***
	(0.112)	(0.112)	(0.108)	(0.108)	(0.116)	(0.108)
Investor exits (Ø, log)	0.018	0.016	0.018	0.019	0.015	0.017
	(0.069)	(0.069)	(0.069)	(0.070)	(0.068)	(0.069)
Year × state FEs	Yes	Yes	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.190	0.190	0.190	0.190	0.190	0.190
Adjusted R-squared	0.158	0.158	0.158	0.158	0.158	0.158
Observations	31,077	31,077	31,077	31,077	31,077	31,077

further regression models. Before we proceed with these regressions, we draw from existing literature and calculate alternative investor heterogeneity measures as described in Section 3.3.4.

Table 3.7 displays the results of our main models using alternative explanatory variables. Columns (1) and (5) show that *Country heterogeneity* has a significant (at the 1% level) impact on the success and amount of funds raised per funding round. A one unit increase in *Country heterogeneity* is associated with an extensive decrease of 36.6% (see column (5)) of funds raised per funding round.

Table 3.7

Robustness to alternative investor heterogeneity measures

This table reports the results of robustness tests and re-estimates the main models (see column (2) of Table 3.3 and Table 3.4). Models (1) and (5) use country heterogeneity, models (2) and (6) geographical distance, models (3) and (7) four factor and models (4) and (8) use seed investor cultural heterogeneity as alternative investor heterogeneity measure. Detailed variable definitions are presented in Table B1 in the appendix. All variables introduced in Table 3.3 and Table 3.4 are defined and calculated identically. As previously, we avoid simultaneity by regressing the contemporaneous dependent variables on the one-series-lagged explanatory variables in all of the analyses. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Successful series financing				Log series financing			
Country heterogeneity	-0.107***				-0.366***			
	(0.026)				(0.099)			
Geographical distance		-0.008***				-0.027***		
		(0.001)				(0.005)		
Cultural heterogeneity (four factors)			-0.064***				-0.212***	
			(0.016)				(0.051)	
Cultural heterogeneity (seed investors)				-0.032***				-0.103***
				(0.006)				(0.015)
Firm age (log)	-0.101***	-0.101***	-0.101***	-0.088***	-0.328***	-0.329***	-0.329***	-0.228***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.024)	(0.024)	(0.024)	(0.022)
Cum. funding rounds (#, log)	-0.134***	-0.134***	-0.133***	-0.226***	-0.366***	-0.363***	-0.363***	-0.603***
	(0.021)	(0.022)	(0.021)	(0.023)	(0.066)	(0.067)	(0.067)	(0.058)
Cum. investors (#, log)	0.024	0.021	0.020	0.074***	-0.000	-0.012	-0.014	0.161***
	(0.016)	(0.017)	(0.017)	(0.018)	(0.057)	(0.060)	(0.060)	(0.054)
Cum. funding (million $, log)	0.058***	0.058***	0.058***	0.074***	0.437***	0.436***	0.435***	0.466***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.025)	(0.025)	(0.025)	(0.028)
Investor age (Ø, log)	-0.040***	-0.041***	-0.041***	-0.043***	-0.140***	-0.142***	-0.141***	-0.128***
	(0.007)	(0.007)	(0.006)	(0.012)	(0.021)	(0.023)	(0.021)	(0.032)
Investor funding rounds (Ø, log)	0.500***	0.510***	0.506***	0.513***	1.460***	1.494***	1.484***	1.447***
	(0.032)	(0.027)	(0.030)	(0.025)	(0.116)	(0.099)	(0.107)	(0.102)
Investor portfolio firms (Ø, log)	-0.520***	-0.529***	-0.526***	-0.553***	-1.465***	-1.496***	-1.486***	-1.518***
	(0.034)	(0.030)	(0.033)	(0.025)	(0.124)	(0.109)	(0.116)	(0.107)
Investor exits (Ø, log)	0.019	0.019	0.018	0.098***	0.019	0.018	0.015	0.266***
	(0.021)	(0.021)	(0.021)	(0.013)	(0.068)	(0.069)	(0.068)	(0.028)
Year × state FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.136	0.135	0.135	0.157	0.190	0.190	0.190	0.228
Adjusted R-squared	0.102	0.101	0.102	0.115	0.159	0.158	0.158	0.190
Observations	31,077	3,1076	31,077	17,595	31,077	31,076	31,077	17,595

Next, we analyse whether the effect of heterogeneous investors on funding success is different when we turn to physical instead of cultural distance among investors. We obtain negative coefficients of -0.008 and -0.027 for $Geographical\, distance$ in columns (2) and (6). Again, the alternative explanatory variable $Geographical\ distance$ is highly statistically significant at the 1% level. This suggests that a large variation in the locations of VCs which accompanies difficulties in the execution and higher effort and costs for physical investor meetings is detrimental to future funding success of investors' portfolio firms.

Following Dai and Nahata (2016), we measure cultural heterogeneity by the four original Hofstede measures - small vs large power distance, uncertainty avoidance, individualism vs collectivism, and masculinity vs femininity. Although the negative relation between $Cultural\ heterogeneity$ $(four\ factors)$, funding success and size weakens slightly in magnitude in comparison to Table 3.3 and Table 3.4, it remains highly statistically significant at the 1% level.

Finally, we consider $Cultural\ heterogeneity\ (seed\ investors)$, i.e., the impact of early shareholder heterogeneity. According to Ferrary (2010), the first funding round, i.e., the seed round, is the "learning by collaborating" period that reduces the information asymmetry between the investor and the entrepreneur. Therefore, we are interested if heterogeneity among seed stage investors, which are frequently characterized by strong ties to entrepreneurs and are usually involved in follow-on investments, has long-term funding implications. We find that despite strong relationships to the investment targets and a high degree of investor involvement (Gompers and Lerner (2004)), the presence of heterogeneous investors at the seed stage represents a 10.3% decline of collected funds in consecutive funding series.

Regarding the coefficients of our control variables, these are predominantly consistent with our main analyses in terms of size and significance. Throughout all models shown in Table 3.7, firm age and investor age, for example, have a negative effect on the success and amount of serial funding rounds. Overall, the findings are reasonable and in line with our prior expectations.

3.5 Concluding discussion

In this paper, we empirically deepen our understanding regarding the implications of heterogeneous investors on funding success in a sample of over 19,000 startups in the US. In line with prior literature, our econometric methodology aims to control for both, a possible survivorship bias in our sample data, and the endogenous nature of VC financing (Colombo and Grilli (2010)).

In accordance with the evidence provided by existing studies in the field of cross-cultural VC research (e.g., Amit et al. (1998), Cumming et al. (2009), Dai et al. (2012), Devigne et al. (2013), Cumming et al. (2016), Chahine et al. (2019)), our findings provide strong support for the notion that culturally divergent VCs represent an obstacle to future entrepreneurial funding success. Furthermore, we make several additional contributions to the literature on entrepreneurial finance and international VC. In particular, we indicate how the heterogeneity of existing investors affects future funding success of startups by hindering VCs' effectiveness to jointly act as a "coach" and provide value to the growth of their portfolio firms.

We highlight the effects of cultural heterogeneity, which represent an obstacle to (i) communication effectiveness, (ii) mutual investor trust, and (iii) the overcoming of homophilia within a heterogeneous group of investors. Moreover, we add to the literature by shedding light on the role and importance of a culturally compatible investor structure throughout the funding phase of a firm. Overall, our findings suggest that it might be worthwhile for entrepreneurs to target a less heterogeneous investor base to ensure future success in follow-on investments. More broadly, our findings emphasize the critical role of investor culture in entrepreneurial financing. While entrepreneurial finance is a high information asymmetry environment by nature, our results reveal that investors imply the cultural fit and concurrent shareholder structure within their investment decision. Therefore, entrepreneurs and investors alike should devote more time and energy to diligently assess the overall cultural fit of potential investments.

Yet, we address the main limitations of our study and identify areas for future research that can potentially improve and extend our knowledge on international VC financing. We can not observe all factors influencing funding success and using secondary data may mask important relationships and interactions among early-stage investors and their targets. As we can not control for all relevant factors, this may violate ceteris paribus condition. Future researchers could shed light on how cultural heterogeneity among VCs affects future ownership and capital structures in the startup industry with the aid of field studies and surveys. Furthermore, the use of funding size to measure serial financing success remains another important limitation of our study. Not all ventures require the same amount of funding to make it to the next developmental stage. Given data availability, future research can capture fundraising performance and the effects of culturally distant investors by gathering additional financial performance data.

Despite the foregoing limitations, this study advances the understanding of the impact of investor heterogeneity on the ensuant funding history of young ventures. Given the results reported here, examining the possible effects in future research more comprehensively would be interesting.

Endnotes

[1] We use the terms diversity and heterogeneity interchangeably.

[2] For a review of the literature on VC syndication, see Jääskeläinen (2012).

[3] For a a review of the literature on VC internationalization, see Devigne et al. (2018).

[4] Dalle et al. (2017) contribute an earlier overall assessment and examples of the use of Crunchbase in management and economics research.

[5] The receipt of capital from heterogeneous investors is endogenous. Startups do not attract financing from individual VCs at random; rather, they may choose investors that provide the best fit given their investor characteristics and industry focus. Moreover, VCs themselves do not chose their investment targets at random, but may invest in portfolio companies of higher quality and chances of success (Devigne et al. (2018)).

[6] For example, a startup has three investors in its first funding, i.e., seed, round: A, B and C. Investor A is located in the US; B is located in Canada and C is based in Singapore. Then, $Geographical\, distance = (0.737 + 15.564 + 14.836) \div 3 = 10.379$.

Appendix

See next page for Table B1.

Table B1
Definition of main variables

This appendix provides definitions and data sources for the main variables used in the study.

Variable	Definition	Source
Panel A: Dependent variables		
Successful series A	A dummy variable that is equal to one if the venture received series A funding and 0 otherwise.	Crunchbase
Successful series B	A dummy variable that is equal to one if the venture received series B funding and 0 otherwise.	As above
Successful series C	A dummy variable that is equal to one if the venture received series C funding and 0 otherwise.	As above
Successful series D+	A dummy variable that is equal to one if the venture received series D, E or F funding and 0 otherwise.	As above
Series A financing (million $)	The natural logarithm of one plus the total amount of million $ funding raised in series A.	As above
Series B financing (million $)	The natural logarithm of one plus the total amount of million $ funding raised in series B.	As above
Series C financing (million $)	The natural logarithm of one plus the total amount of million $ funding raised in series C.	As above
Series D+ financing (million $)	The natural logarithm of one plus the total amount of million $ funding raised in series D, E and F.	As above
Panel B: Investor heterogeneity measures		
Cultural heterogeneity	A measure of cultural heterogeneity between VCs based on the six Hofstede measures of culture (i.e., power distance, individualism, masculinity, long-term orientation, indulgence and uncertainty avoidance), as used in Dai and Nahata (2016) and Khurshed et al. (2020). The data stem from Geert Hofstede's website `www.geerthofstede.nl`.	Authors' calculations based on Crunchbase and Hofstede data
Cultural heterogeneity (four factors)	A measure of cultural heterogeneity between VCs based on the four original Hofstede measures of culture (i.e., power distance, individualism, masculinity and uncertainty avoidance).	As above
Cultural heterogeneity (seed investors)	A measure of cultural heterogeneity between seed-stage VCs based on the six Hofstede measures of culture as described above.	As above
Country heterogeneity	A measure of country heterogeneity between VCs based on Blau (1977)'s index of heterogeneity, i.e., $1-\sum_{a\in A} {P_a}^2$ where A is the number of country groups, and P_a is the proportion of country population in group a.	Authors' calculations based on Crunchbase data
Geographical distance	A measure of geographical distance (in thousand km) between capitals of the respective countries of VCs invested in the firm.	Authors' calculations based on Crunchbase and CEPII data
Panel C: Firm characteristics		
Firm age (log)	The natural logarithm of one plus the number of years since the firm was founded. It is often used as a proxy for a firm's establishment in the market (Colombo and Grilli (2010), Devigne et al. (2013), Vismara (2019), Croce et al. (2023)).	Authors' calculations based on Crunchbase data

(*continued*)

Table B1 — *continued*

Variable	Definition	Source
Cum. funding rounds (#, log)	The natural logarithm of one plus the total number of all funding rounds already conducted by the firm (Arroyo et al. (2019)).	As above
Cum. investors (#, log)	The natural logarithm of one plus the total number of all investors currently engaged in the venture. It is often used as a proxy for financial success in firms' financing phases (Signori and Vismara (2018), Arroyo et al. (2019), Croce et al. (2023)).	As above
Cum. funding (million $, log)	The natural logarithm of one plus the cumulative funding raised by the firm (in million $) (Block and Sandner (2009), Arroyo et al. (2019)).	As above
Panel D: Investor characteristics		
Investor age (Ø, log)	The natural logarithm of one plus the average number of years since the investment entity was founded (Sorenson and Stuart (2001), Nahata et al. (2014)).	As above
Investor funding round (Ø, log)	The natural logarithm of one plus the average number of all previously conducted funding rounds of all investors currently engaged in the firm (Alexy et al. (2012), Arroyo et al. (2019)).	As above
Investor portfolio firms (Ø, log)	The natural logarithm of one plus the average number of portfolio firms held by investors currently engaged in the firm (Croce et al. (2023)).	As above
Investor exits (Ø, log)	The natural logarithm of one plus the average number of portfolio firms exited via an IPO or acquisition by the end of 2022. It is often used as a proxy for VC investment success (Bottazzi et al. (2008), Dai and Nahata (2016), Khurshed et al. (2020)).	As above

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CHAPTER 4

On the Impact of Sustainable Venture Capital

WITH

M. MÖNKEMEYER AND H. SCHRÖDER

Abstract

Investment by venture capitalists (VCs) that have signed the United Nations Principles for Responsible Investment (PRI) positively affects startups' environmental performance. Our findings are based on a comprehensive sample of new ventures that went public during the 2010–2022 period. To capture startups' environmental properties in the funding phase, we adapt the machine learning approach of Mansouri and Momtaz (2022). Late adopters of the PRI enhance environmental performance significantly less than early adopters, indicating potential free-riding behavior. Additional analysis reveals that the impact of PRI ownership on environmental performance is weaker for ventures that are already highly sustainable and stronger for ventures in environmentally sensitive countries. Finally, we find that exposure to PRI VCs during the funding stage shapes startups' long-term environmental performance.

4.1 Introduction

Traditionally, the sole objective of entrepreneurial ventures has been to create financial value for its shareholders. However, over the decades and in particular during the recent years, the traditional concept of shareholder value has been more and more replaced by an integrated view on entrepreneurial value creation – one that incorporates social and environmental externalities. This integrated view on entrepreneurial activities is commonly referred to as sustainable entrepreneurship (Shepherd and Patzelt (2011)) and has become an increasingly important subfield of entrepreneurship research.[1]

One question that is of particular importance in this strand of literature is the one after the underlying determinants and driving factors of entrepreneurial sustainability orientation. While most studies on environmental and social issues in the context of entrepreneurial ventures focus on the role of the entrepreneur, only a very few studies address social entrepreneurship from the investors' perspective. To the best of our knowledge, only Vismara (2019) and, most recently, Mansouri and Momtaz (2022), analyse the financial implications of sustainable entrepreneurship and assess the value implications of ventures' sustainability orientation in crowdfunding campaigns and initial coin offerings, respectively. These studies document ambiguous effects. While Vismara (2019) finds no relation between sustainability performance and funding success in crowdfunding campaigns, Mansouri and Momtaz (2022) document a positive effect for funding success but a negative impact on long-term performance. In line with this finding for venture performance, Barber et al. (2021) document reduced financial performance for impact-oriented venture capital funds compared to their traditional counterparts.

However, beyond this initial evidence little is known about the relevance of entrepreneurial sustainability-orientation for venture capitalists (VCs). In contrast, there exists substantial evidence in the field of public equity investments that environmental and social issues are highly relevant for institutional investors. For example, Krueger et al. (2020) provide survey evidence on climate risk perceptions among institutional investors and find they view climate risks as relevant to their investment process. These results further support the notion that especially larger and sustainability-oriented funds believe that active engagement is a key instrument to address environmental issues at the firm-level. These findings are also in line with the recent empirical evidence on the active impact of institutional ownership on corporate environmental performance (see, for example, Dyck et al. (2019), Chen et al. (2020)).

In their engagement, institutional investors have formed coalitions on long-term sustainable investment. These coalitions include, for example, Focusing Capital on the Long-Term Global (FCLT-Global), the Global Impact Investing Network (GIIN), and the United Nations Principles for Responsible Investment (PRI). Its signatories (members) agree to (i) incorporate sustainability issues into their investment analysis and decision making process, (ii) act as active owners that incorporate sustainability issues into their ownership policies, and (iii) foster voluntary disclosure on sustainability issues by their portfolio firms (UNPRI (2023a)). Recent evidence highlights the impact of this joint engagement. For example, Dyck et al. (2019) show that sustainability-committed investors that are signatories to United Nations PRI have more than double the average investor impact on firms' environmental and social performance.

Given the documented impact of sustainability-oriented investors in the domain of public equity, the question arises whether institutional funding has similar effects in entrepreneurial finance. Specifically, this study aims to shed light on the role of sustainable VCs. Given the increasing relevance of PRI commitments in the private equity and venture capital landscape, we follow the recent literature (Dyck et al. (2019)) and classify VCs who are signatories to this coalition as committed sustainable investors. Our study focuses on the environmental performance impact of sustainable VCs in early-stage ventures. However, it is also crucial to understand whether and how VCs shape the long-term environmental responsibility of ventures once they have transformed into established firms.

Using a comprehensive sample of early-stage ventures and corresponding investor information, we explicitly model the impact of sustainable VCs on ventures' environmental performance. Measuring environmental performance in startups is a major challenge as commercial environmental, social and corporate governance (ESG) ratings are rarely available for early-stage firms. To quantify ventures' environmental performance, we follow Cumming et al. (2022) and adapt the recent approach introduced by Mansouri and Momtaz (2022). Specifically, we apply their algorithm to extract a measure of environmental performance at the firm-year level using all information available in ventures' Twitter feeds. This allows us to run panel regressions to identify the impact of sustainable VCs on entrepreneurial environmental performance. Controlling for sources of observed and unobserved heterogeneity across firms, industries, and time we are able to document a statistically significant and economically meaningful impact of PRI-compliant VCs on startups' environmental performance. This holds especially for VCs that documented a strong commitment to the approach of sustainable investment by being early adopters of the PRI. We further show that the impact of sustainable VCs is greater in firms with relatively low environmental performance levels, i.e., those firms with a high upside in environmental performance. Using post-IPO environmental performance ratings provided by the commercial data vendor Thomson Reuters (TR), we are able to confirm this impact of sustainable VCs in the long-run – up to several years after the firms' IPO. All key results of our study remain robust after accounting for potential endogeneity concerns in the estimation process.

The remainder of this paper is organized as follows. In Section 4.2, we provide a literature review and discuss our main hypotheses. Section 4.3 describes our data and research methods. Section 4.4 presents our empirical results regarding the effect of PRI ownership on environmental performance. Section 4.5 concludes the paper.

4.2 Related literature and hypotheses

4.2.1 Environmental firm performance

Traditional accounting practices do not provide sufficient information for environmental decision making. ESG performance measures fill this gap by capturing additional dimensions of corporate performance that are not adequately reflected in financial data (Jasch (2006)). However, there is disagreement in the literature about how to measure ESG and, in particular, how to aggregate its different components into a composite measure (see, for example, (Chatterji et al. (2016), Brandon et al. (2021), Berg et al. (2022), Mansouri and Momtaz (2022)). Although the literature recognizes that the elements of ESG are inevitably interrelated, most studies focus on individual aspects of ESG (de Villiers et al. (2022)).

Our study focuses on the environmental element, that is, the "E" in ESG. We do this for a number of reasons. First, given the rapid degradation of global ecosystems, internal and external stakeholders are increasingly demanding that firms take responsibility for their environmental footprint and develop climate change strategies and targets (Starik and Marcus (2000), Jasch (2006), Velte (2019)). It is already well known that the warming of the atmosphere, oceans, and land is due to human influence. Energy consumption, waste production, and resource demand are all linked to environmental issues. With the 2015 Paris Agreement's goal of reducing emissions and combating climate change in danger of failing, the public discussion primarily focuses on firms' environmental aspects and their economic consequences.

Moreover, there is an ongoing debate in the academic literature about the importance of environmental management activities for firms' economic success and competitiveness. Most studies report a positive relation between environmental and economic performance.[2] For example, Bauckloh et al. (2021) show that ventures with high environmental performance benefited from "insurance-like protection" during and directly after the 2007–2008 financial crisis. Hence, a high level of environmental performance can partly substitute for a startup's lack of a strong earnings history. By pursuing and communicating about environmental projects, entrepreneurs can overcome the liability of novelty and create a positive reputation among stakeholders (Bird and Schjoedt (2017)).

Taken together, the literature confirms the importance of corporate environmental action from both a societal and an economic perspective. Highly environmental firms signal their understanding of long-term strategic issues to the market. They demonstrate their ability to manage long-term goals by adapting to global challenges and addressing stakeholders' changing demands. However, despite the importance of environmental action, the literature neglects to analyse the factors that shape sustainability performance in the early stage of entrepreneurial ventures.

4.2.2 Investor capabilities of enhancing environmental firm performance

Our study joins the burgeoning entrepreneurial finance literature that examines the role of institutional investors in promoting sustainable development. Large institutional investors such as pension funds, insurance companies, finance firms, and university endowments frequently run venture capital (VC) funds. VC represents a special segment of the private equity (i.e., institutional investor) industry because institutions typically invest only a small percentage of their total assets under management in high-potential but high-risk ventures (Zider (1998)). VCs actively promote and add value to the development of startups and participate in future earnings (Sahlman (1990)).

The literature conceptualizes the abilities of VCs to contribute to the creation and growth of startups in different ways (see, for example, (Yang et al. (2009), Colombo and Grilli (2010), Meglio et al. (2017)). Yang et al. (2009) argue that VCs require both *screening* and *evaluation* capabilities to generate short-term financial returns or long-term strategic returns. Screening refers to VCs' ability to identify promising startups, whereas evaluation focuses on VCs' ability to accurately price startups. Colombo and Grilli (2010) emphasize VCs' *scouting* capability, which captures their ability to identify startups with superior competitive potential and provide them with the required financial resources. Given that VCs use their venture-building experience and industry expertise to actively monitor startups, Meglio et al. (2017) differentiate between *scouting* and *coaching* capabilities. *Scouting* refers to VCs' ability to identify firms whose hidden value they can unlock by reducing financial constraints. *Coaching,* in contrast, builds on knowledge transfer and goes beyond the provision of funding.

So far, little attention has been paid to the “E” within active ownership (Cheng et al. (2022)), which is surprising in light of Majoch et al. (2012), who argue that ESG-driven active ownership is the most effective channel for influencing investee firms. In addition, aspects of sustainability have become an important part of VCs' pre-investment due diligence because of increasing climate change awareness and political pressure to lower greenhouse gas emissions. Moreover, the field of sustainable investing in dedicated ESG startups, also referred to as *impact investing,* is experiencing soaring growth in both research and practice (Agrawal and Hockerts (2021), Gillan et al. (2021), Barber et al. (2021)), highlighting the importance of VC in the funding dilemma of environmentally sustainable startups (Margolis and Walsh (2003), Parris and Demirel (2010), Petkova et al. (2014)). Finally, the scale of investment flows suggests that consideration of environmental factors is much more than a fad. Sustainable investments increased by 55% over the 2016–2020 period, accounting for 35.9% (US$35.3 trillion) of all professionally managed assets (Global Sustainable Investment Alliance (2020)).

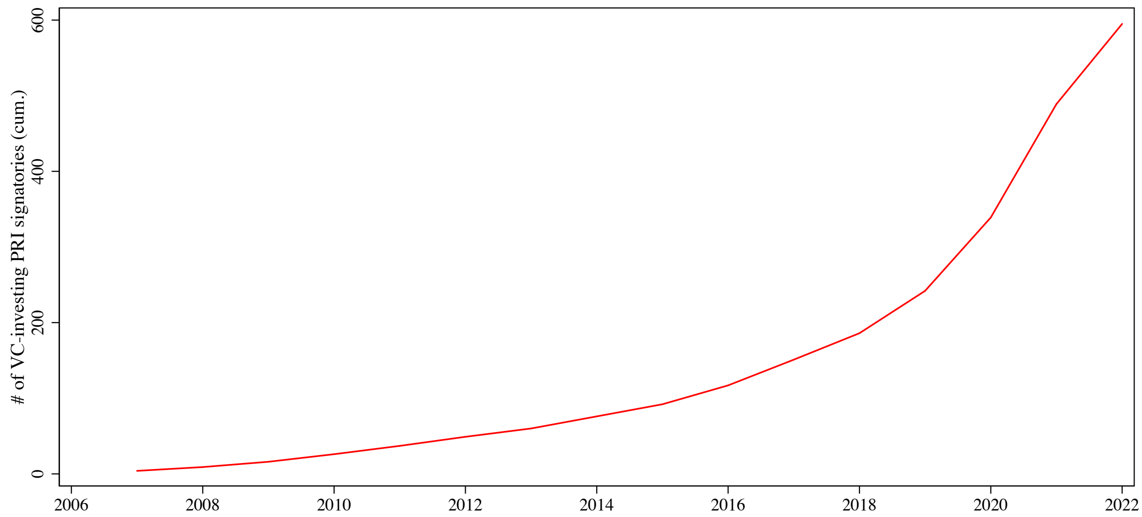
Although academia has not kept pace with practitioners' growing interest in startups' environmental performance,[3] voluntary initiatives such as the United Nations PRI have gained widespread popularity in recent years. Initiated in 2006 by a group of investors, the PRI network postulates the need for an economically efficient, sustainable global financial system for long-term value creation.[4] As one of the world's leading advocates for responsible investment, the PRI aims to facilitate the inclusion of environmental factors in investment decisions, thereby supporting the sustainable transformation of society by directing financial flows to sustainable firms (UNPRI (2023a)). Figure 4.1 illustrates the rapid growth in the number of PRI VC investors and their participation in funding rounds since the launch of the initiative. In October 2022, there were more than 5,200 PRI signatories. VC investors account for approximately 600 signatories, and more than 8,300 VC funding rounds have attracted at least one PRI VC signatory investor.

Building on the above literature, we conjecture that PRI ownership is an important determinant of startups' environmental performance. We therefore hypothesize as follows:

Hypothesis (H1): *The presence of PRI investors is positively related to firms' environmental performance in the funding phase.*

If PRI VC investors exercise their coaching capability during startup funding phases, it is conceivable that knowledge spillovers could manifest in improved long-term environmental performance. Although coaching occurs only during the investment period of VCs, that is, during the pre-IPO stage, research suggests that actions taken during this early phase can shape ventures' long-term behavior (Bamford et al. (2000)). We assume that PRI investors' contributions to startups' environmental business practices persist after their exit (Boeker (1989)).

(a) PRI VC-investing signatories over time



(b) PRI VC funding rounds over time

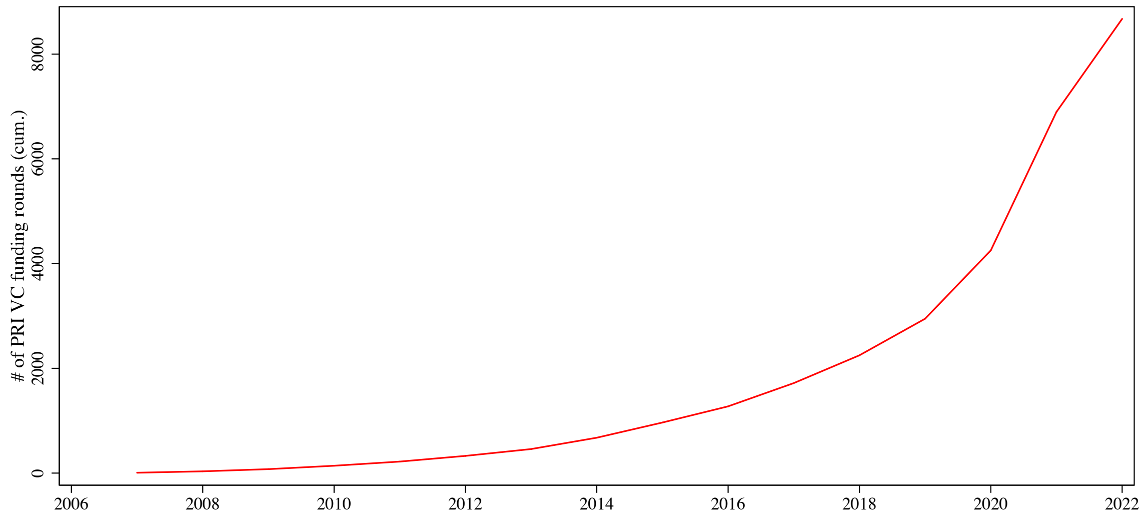


Figure 4.1. Sustainable investor activity. This figure shows investment activity by venture capitalists (VCs) that have signed the United Nations Principles for Responsible Investment (PRI). Figure 4.1a reports the cumulative number of PRI VCs by year. Figure 4.1b shows the cumulative number of funding rounds that involve at least one PRI signatory VC.

Accordingly, we propose the following hypothesis:

Hypothesis (H2): *The presence of PRI investors is positively related to firms' environmental performance in the post-IPO phase.*

4.3 Data and methodology

4.3.1 Sample

We collect data from four major sources: Crunchbase, Twitter, the TR ESG database, and the PRI signatory database. We start by extracting venture information from Crunchbase (`www.crunchbase.com`, accessed in October 2022). Crunchbase is widely used in management research (see, for example, Block and Sandner (2009), Ter Wal et al. (2016), Seigner et al. (2023)). It provides global, publicly available data on startups, entrepreneurs, and investors. It also includes funding histories and exit information. We retrieve data on 187,898 ventures funded by 51,266 non-private investors (primarily VCs) in 349,909 funding rounds over the 2010–2022 period.

We investigate the impact of PRI investors on firms' environmental performance in both the funding and the post-IPO stages. Therefore, we retain firm-years that are active on Twitter in the funding phase or covered by the TR ESG database in the post-IPO stage. We draw firms' communication history from their official Twitter accounts (`www.twitter.com`, accessed in October 2022) and obtain their TR sustainability-pillar scores.

For the construction of our key explanatory variables, we retrieve information on PRI signatories from the initiative's website (`www.unpri.com`, accessed in October 2022), including the signatories' names, signature dates, and headquarters countries.

Our final funding-stage sample consists of 887 firm-years representing 200 distinct startups. The post-IPO analyses are based on a cross-section of 341 firms as not all startups are active on Twitter during the VC funding-stage.

4.3.2 Measurement of environmental performance

4.3.2.1 Measurement of startups' environmental performance in the literature

Establishing a link between VC investment and firms' environmental performance is challenging because VCs are mainly involved at the beginning of a firm's life cycle, whereas commercial ESG databases such as the TR ESG database typically cover mature firms (Cheng et al. (2022)).

The literature has yet to find ways to meaningfully capture startups' ESG properties (Anand et al. (2021), Mansouri and Momtaz (2022)). Existing proxies are commonly prone to subjectivity issues. Scholars generally capture startups' sustainability performance in an ad hoc manner using keywords in project descriptions (Vismara (2019)) or adhere to the self-classifications of entrepreneurs and their investors as "environmentally oriented" (e.g., Hörisch (2015), and Barber et al. (2021)). As Grewal and Serafeim (2020, p. 20) put it, improving measures of corporate sustainability would be "[...] *the single biggest opportunity for researchers to advance the field.*"

Recent work by Mansouri and Momtaz (2022) overcomes this limitation by introducing a text-based machine learning approach (we elaborate on their methodology in Section 4.3.2.2). Their approach facilitates comparability across ESG studies and addresses the limitations of the subjectivity and singularity of ad hoc measures. The use of text mining techniques to operationalize qualitative information, such as website statements, has led to empirical breakthroughs in various research fields (e.g., Tennyson et al. (1990), Archak et al. (2011), Netzer et al. (2012), Kaplan and Vakili (2015)).

4.3.2.2 Measurement of startups' environmental performance in the funding phase

To quantify startups' environmental performance in the funding phase, we follow Cumming et al. (2022) and adapt the recent approach introduced by Mansouri and Momtaz (2022). Their machine learning algorithm uses an ESG-specific dictionary (i.e., a word list) in the startup context to construct ESG ratings from text data. The algorithm provides composite ESG performance scores and scores disaggregated by dimension, including the environmental dimension. All scores are normalized to the size of the dictionary.

We perform sanity checks and observe strong correlations with the TR ESG score. This step demonstrates the external validity of their method and confirms that their approach reliably captures the ESG properties of both startups and mature firms.[5] After retrieving annual Twitter data for our sample firms, we run their machine learning algorithm to obtain our proxy for startups' environmental performance in the funding phase at an annual frequency, which we denote by $E\text{-}score(normalized)$.

4.3.2.3 Measurement of startups' environmental performance in the post-IPO phase

To capture startups' environmental performance in the post-IPO stage, we rely on the TR ESG database. The data best meet our study requirements in terms of coverage, scope, and methodology. Moreover, TR ESG scores are widely used in the literature (Beiting et al. (2014), Luo et al. (2015), Chatterji et al. (2016), Ferrell et al. (2016), Ghoul et al. (2017), Bauckloh et al. (2021), among others) and in practice, since investors also frequently incorporate TR ESG scores into their investment decisions.[6]

TR evaluates the ESG performance of firms based on publicly available information such as annual reports, corporate social responsibility (CSR) reports, company websites, and news sources. They contain more than 700 non-financial data points to quantify corporate performance in 10 key areas within each of the environmental, social, and governance dimensions. Based on these data, a category score is calculated for each dimension using a percentage ranking methodology and industry and country benchmarking. The category scores are then aggregated into four high-level pillar scores, including the environmental pillar score. We use this score as a proxy for startups' environmental performance in the post-IPO phase, which we denote by $Environmental\ pillar$.

4.3.3 Sustainable VC investors

To capture a startup's exposure to VC PRIs, for each firm-year, we compute the ratio of PRI signatories to all currently engaged investors, which we denote by $Own.\ PRI\ investors\,(\%)$. We also apply a variety of alternative measures as part of our robustness tests in Table 4.6. For a detailed description of our definitions and data sources, see Table C1 in the appendix.

4.3.4 Control variables

Based on a careful review of the literature, we construct a vector of control variables on firm and investor characteristics, which we denote by Ω. For brevity, we refer to Appendix Table C1.

4.3.5 Econometric approach

To test whether the presence of PRI investors is associated with higher environmental performance in the funding phase (that is, H1), we estimate several specifications of the following regression:

$$\begin{aligned} E\text{-}score\,(normalized)_{it} = \beta Own.\,PRI\,investors\,(\%)_{it-1} + \gamma\Omega_{it-1} \\ + FEs + \varepsilon_{it}, \end{aligned} \tag{4.1}$$

where $E\text{-}score\,(normalized)_{it}$ is the environmental performance of venture i in year t; $Own.\,PRI\,investors\,(\%)_{it-1}$ is the percentage of PRI signatories among all investors currently engaged in venture i in year $t-1$; and Ω_{it-1} is a vector of time-varying control variables of firm and investor characteristics for venture i in year $t-1$. FEs are year fixed effects (hereafter, FEs), firm FEs, and year × industry FEs. We cluster heteroskedasticity-robust standard errors at the country level.

As in related entrepreneurial finance studies (Colombo and Grilli (2010), Bertoni et al. (2011), Fisch and Momtaz (2020), Sun et al. (2020), Mansouri and Momtaz (2022)), endogeneity is a concern to our inferences. We are interested in the treatment effect of PRI funding on ventures' environmental performance. However, reverse causality posits that highly sustainable firms attract funding from PRI investors. To obtain valid inferences, we avoid simultaneity by regressing contemporaneous values of $E\text{-}score\,(normalized)$ on one-year lagged values of $Own.\,PRI\,investors\,(\%)$ and Ω (see Equation 4.1).

To allay any remaining doubts about violations of the exogeneity condition (i.e., $E[\Omega_{it-1}, \varepsilon_i] \neq 0$), we address sample selection bias by controlling for selection based on both observed and unobserved heterogeneity. Following above literature, we estimate different two-stage approaches. We start by sorting all values of $Own.\,PRI\,investors\,(\%)$ in our sample by year to distinguish between firms with a low share versus firms with a high share of PRI investors based on the median ($many\,PRI_{it}$). We then estimate a probit model to explain the probability that firm i belongs to the subsample of high-PRI ownership firms in year t. The independent variables in this model are captured by a vector of exogenous firm and investor characteristics, denoted by $\Omega^{(s)}_{it-1}$. Formally, we estimate as follows:

$$many\,PRI_{it} = \delta\Omega^{(s)}_{it-1} + \xi_{it} \tag{4.2}$$

Building on Equation 4.2, we address sample selection bias in two distinct ways. First, we follow the literature (Colombo and Grilli (2010), Sun et al. (2020), Mansouri and Momtaz (2022)) and control for “selection on observables” by adapting a typical two-stage Heckman correction model (Heckman (1979)). In the first step, we obtain the predicted individual probabilities from Equation 4.2 and compute inverse Mills ratios (IMRs) for the selection of ventures into PRI ownership:

$$IMR_{it} = \frac{\phi(\frac{\delta\Omega_{it}^{(s)}}{\sigma_{\xi_{it}}})}{\Phi(\frac{\delta\Omega_{it}^{(s)}}{\sigma_{\xi_{it}}})}, \tag{4.3}$$

where IMR_{it} is the IMR of venture i in year t; and $\phi(.)$ and $\Phi(.)$ are the probability density and the cumulative density of the standard normal distribution, respectively. Next, we incorporate the (one-year lagged) IMR as an additional explanatory variable into the baseline model (see Equation 4.1) to partial out a possible selection effect, λ. More formally,

$$\begin{aligned} E\text{-}score\,(normalized)_{it}^{IMR} = \beta Own.PRI\,investors\,(\%)_{it-1} + \lambda IMR_{it-1} \\ + \gamma\Omega_{it-1} + FEs + \upsilon_{it}, \end{aligned} \tag{4.4}$$

Second, we control for “selection on unobservables” by using an adjusted instrumental variables approach. Consistent with Gourieroux et al. (1987) and Mansouri and Momtaz (2022), we obtain the generalized residuals (GRs) from Equation 4.2 and use them to instrument ventures’ PRI ownership. Formally, we define

$$GR_{it} = many\,PRI_{it} \times \frac{\phi(-\delta\Omega_{it}^{(s)})}{1-\Phi(-\delta\Omega_{it}^{(s)})} + (1 - many\,PRI_{it}) \times \frac{-\phi(\delta\Omega_{it}^{(s)})}{\Phi(-\delta\Omega_{it}^{(s)})}, \tag{4.5}$$

where GR_{it} are the GRs of venture i at time t.

Next, we turn to the association between PRI ownership and long-run environmental performance (that is, H2). We estimate different cross-sectional regressions of the following type:

$$Environmental\,pillar_{it} = \eta + \theta Own.PRI\,investors\,(\%)_i + \iota\Omega_i + FEs + \rho it, \tag{4.6}$$

where $Environmental\,pillar_{it}$ is the environmental performance of venture i in the year of its IPO t; $Own.PRI\,investors\,(\%)_i$ is the percentage of PRI signatories among all investors engaged in venture i, measured in the last year prior to its IPO; and Ω_i is a vector of static control variables of firm and investor characteristics for venture i, measured in the last year prior to its IPO. FEs are year FEs.

4.3.6 Summary statistics

We present the summary statistics of our main variables in Table 4.1. Environmental performance varies considerably among the sample firms. It ranges from 0 to 6.496, with a mean of 0.976 and a standard deviation of 1.375. We also report the descriptive statistics of the main explanatory variables, firm and investor characteristics, but for the sake of brevity, we do not comment on them.

To provide an initial overview of how firm and investor characteristics differ between ventures with and without PRI signatories, we turn to the univariate statistics in Table 4.2. In the first step, we split the sample based on whether at least one PRI signatory is invested. We then observe and test for differences between the two subsamples.

Focusing on environmental performance, we find that on average, PRI-invested ventures show a normalized E-score of 1.477. The corresponding effect for the subsample of firm-years without PRI investors is significantly lower at 0.913. The mean difference between both groups at 0.565 is statistically significant at the 1% level, indicating that the presence of PRI signatories is associated with higher environmental performance.

Next, we examine whether firm and investor characteristics provide preliminary evidence on why environmental performance differs between PRI-funded and non-PRI funded ventures. Turning to firm characteristics, we find that the presence of PRI signatories is associated with more funding rounds (7.424 vs. 3.514), higher funding volumes (1.515 \$B vs. 0.098 \$B), and greater communication intensity (30.371 words vs. 12.513 words). The mean differences in means are significant at the 1% level. PRI-funded ventures are also slightly older on average (8.131 years vs. 7.912 years). However, with a p-value of 0.666, the t-test for no differences in means cannot be rejected due to a lack of statistical significance.

In terms of investor characteristics, we find that PRI-funded ventures have more investors overall (26.980 vs. 10.100), but that their investors are on average less likely to be domestic (0.841% vs. 0.882%) and involved in fewer funding rounds (1.726 vs. 26.738). The mean differences are statistically significant at the 1%, 10%, and 5% levels, respectively. Given the lack of statistical significance, there are no discernable differences in investors' age (9.211 years vs. 11.261 years, $p = 0.104$) or in their average number of portfolio firms (2.077 vs. 106.374, $p = 0.162$).

Table 4.1
Descriptive statistics

This table reports the descriptive statistics of the main variables used in the study. It reports the number of observations (N), mean, standard deviation (SD), first percentile (P1), fifth percentile (P5), median, 95th percentile (P95), and 99th percentile (P99). All continuous variables are winsorized at the first and 99th percentiles to constrain the impact of spurious outliers. Panel A reports the descriptive statistics of our dependent variable, that is, the normalized environmental score. Panel B reports the descriptive statistics of our key explanatory variables. Panels C and D report the descriptive statistics of firm characteristics and investor characteristics, respectively. The sample consists of 887 firm-year observations (representing 200 unique firms) over the 2010–2022 period. For a detailed description of our definitions and data sources, see Table C1 in the appendix.

	N	Mean	SD	P1	P5	Median	P95	P99
Panel A: Dependent variable								
E-score (normalized)	887	0.976	1.375	0.000	0.000	0.394	4.134	6.496
Panel B: Key explanatory variables								
Own. PRI investors (%)	887	0.005	0.023	0.000	0.000	0.000	0.037	0.143
Own. PRI investors (#)	887	0.108	0.453	0.000	0.000	0.000	1.000	2.000
PRI investor (dummy)	887	0.069	0.253	0.000	0.000	0.000	1.000	1.000
Own. E-friendly investors (%)	887	0.102	0.153	0.000	0.000	0.000	0.417	0.526
Panel C: Firm characteristics								
Funding rounds	887	3.950	3.040	1.000	1.000	3.000	9.000	17.000
USD raised (in B)	887	0.256	1.529	0.001	0.001	0.044	0.566	3.613
Communication intensity (in K)	887	14.506	55.936	0.001	0.001	2.871	50.622	158.246
Firm age	887	7.937	4.753	1.000	2.000	7.000	16.000	23.000
Panel D: Investor characteristics								
Investor age (Ø)	887	11.032	11.845	1.000	1.286	8.429	27.333	51.750
Domestic investors (%)	887	0.877	0.226	0.000	0.400	1.000	1.000	1.000
Total investors	887	11.984	11.548	2.000	2.000	8.000	34.000	58.000
Investor funding rounds (Ø)	887	23.947	113.107	1.080	1.150	1.889	91.000	565.000
Investor portfolio firms (Ø)	887	94.734	699.873	1.174	1.320	2.787	155.000	2,621.000

Table 4.2
Univariate statistics

This table reports the univariate statistics of the main variables used in the study. Column (1) shows the variable means for firm-years in which at least one PRI signatory is invested, and column (2) reports the sample means for firm-years without any PRI investor engagement. We perform the sample split based on the $PRI\ investor(dummy)$ variable. Column (3) reports the mean differences of the subsamples. Column (4) reports the p-values of t-tests in which we test for differences in means between the subsamples and report their p-values. Panel A reports the univariate statistics of our dependent variable, that is, the normalized environmental score. Panels B and C report the univariate statistics of firm characteristics and investor characteristics, respectively. The sample consists of 887 firm-year observations (representing 200 unique firms) over the 2010–2022 period. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For a detailed description of our definitions and data sources, see Table C1 in the appendix.

	(1) invested	(2) not inv.	Δ (1) - (2)	p-value Δ
Panel A: Environmental performance				
E-score (normalized)	1.477	0.913	0.565	0.000***
Panel B: Firm characteristics				
Funding rounds	7.424	3.514	3.910	0.000***
USD raised (in B)	1.515	0.098	1.418	0.000***
Communication intensity (in K)	30.371	12.513	17.858	0.003***
Firm age	8.131	7.912	0.219	0.666
Panel C: Investor characteristics				
Investor age (Ø)	9.211	11.261	-2.051	0.104
Domestic investors (%)	0.841	0.882	-0.041	0.087*
Total investors	26.980	10.100	16.880	0.000***
Investor funding rounds (Ø)	1.726	26.738	-25.012	0.038**
Investor portfolio firms (Ø)	2.077	106.374	-104.297	0.162

4.4 Empirical results

4.4.1 Baseline

To test whether the presence of PRI investors is associated with improvements in corporate environmental performance during the financing phase (that is, H1), we estimate Equation 4.1. The results are reported in Table 4.3.

In the first model, we regress contemporaneous values of $E\text{-}score\,(normalized)$ on one-year lagged values of $Own.PRI\,investors(\%)$ and the vector of firm and investor control variables specified in Section 4.3.4. We add firm and year FEs to the model to control for unobserved heterogeneity at the firm level and across time, respectively. As can be seen from column (1), the coefficient on $Own.\,PRI\,investors\,(\%)$ is positive and statistically significant at the 1% level. These results support H1 and indicate that a higher share of PRI signatories among firms' investors is associated with higher environmental performance at the firm level.

Table 4.3
Baseline results

This table reports the results of the regressions of startups' environmental performance on ownership by venture capitalists (VCs) that have signed the United Nations Principles for Responsible Investment (PRI), along with the control variables. Model (1) controls for unobserved heterogeneity at the firm level and across time via firm and year fixed effects (FEs). Model (2), the baseline model, replaces year FEs with year × industry FEs to control for common industry trends that may correlate with PRI ownership (see Equation 4.1). Column (3) uses the first-difference estimator instead of the FE estimator. Columns (4)-(6) address the selection effects. Columns (4) and (5) estimate the first- (see Equation 4.2) and second-stage (see Equation 4.4) Heckman correction model. Column (6) uses the generalized residuals (see Equation 4.5) to instrument PRI ownership. We regress contemporaneous dependent variables on the one-year-lagged explanatory variables to avoid simultaneity. We cluster heteroskedasticity-robust standard errors at the country level. These are reported in parentheses. See Table C1 for definitions of variables.

	(1)	(2)	(3)	(4)	(5)	(6)
Model:	Main		Δ	Selection	IMR	IV
Dependent variable:	E-score (norm.)$_t$			$1_t^{\text{many PRI}}$	E-score (norm.)$_t$	
Own. PRI investors (%)$_{t-1}$	2.276∗∗∗	1.988∗∗∗	1.788∗		1.860∗∗∗	21.828∗∗∗
	(0.338)	(0.403)	(0.890)		(0.400)	(4.467)
Funding rounds$_{t-1}$	0.027∗∗	0.050∗∗∗	0.059∗∗∗	-0.002	0.044∗∗∗	0.043∗∗∗
	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)
USD raised (log)$_{t-1}$	0.076∗∗	-0.000	0.038	0.334∗∗∗	0.015	-0.020
	(0.029)	(0.033)	(0.023)	(0.029)	(0.028)	(0.027)
Communication intensity (log)$_{t-1}$	0.091∗∗∗	0.090∗∗∗	0.366∗∗∗	0.001	0.095∗∗∗	0.100∗∗∗
	(0.012)	(0.012)	(0.034)	(0.010)	(0.010)	(0.011)
Firm age (log)$_{t-1}$	-0.184∗∗	-0.224∗	0.043	-0.088∗∗∗	-0.215∗	-0.146
	(0.071)	(0.125)	(0.059)	(0.018)	(0.119)	(0.103)
Investor age (Ø, log)$_{t-1}$	0.130∗∗∗	0.131∗∗∗	-0.004	0.303∗∗∗	0.147∗∗∗	0.122∗∗∗
	(0.019)	(0.019)	(0.009)	(0.018)	(0.014)	(0.016)
Domestic investors (%)$_{t-1}$	0.377∗∗∗	0.401∗∗	0.038	-0.687	0.365∗∗	0.328
	(0.112)	(0.135)	(0.123)	(0.466)	(0.128)	(0.338)
Total investors (log)$_{t-1}$	0.111	0.078	-0.127∗∗	0.785∗∗∗	0.090	-0.077
	(0.106)	(0.095)	(0.042)	(0.108)	(0.093)	(0.083)
Investor funding rounds (Ø, log)$_{t-1}$	0.254∗∗∗	0.305∗∗∗	-0.061∗	0.294	0.332∗∗∗	0.351∗∗∗
	(0.046)	(0.025)	(0.032)	(0.215)	(0.037)	(0.036)
Investor portfolio firms (Ø, log)$_{t-1}$	-0.163∗∗	-0.298∗∗∗	0.108∗∗∗	-0.262	-0.328∗∗∗	-0.410∗∗∗
	(0.054)	(0.022)	(0.033)	(0.262)	(0.033)	(0.038)
Year FEs	Yes	No	No	No	No	No
Year × industry FEs	No	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	No	No	Yes	Yes
Adjusted R-squared	0.568	0.593	0.227	n/a	0.594	0.558
Observations	887	887	800	887	887	887

Next, in column (2), we replace year FEs with year × industry FEs to control for any common industry trends that may correlate with PRI ownership and confound our results. We notice an increase in the model fit (adjusted R^2 of 0.593 vs. 0.568) and a slight decrease in magnitude of the coefficient on $Own.PRI\,investors$ (%) (1.988 vs. 2.276). This indicates that unobserved heterogeneity at the industry-year level indeed affects our inferences. Importantly, in this specification (hereafter referred to as the baseline model) the coefficient on PRI ownership remains highly statistically significant at the 1% level. In terms of economic effect size, the estimate implies that a one standard deviation increase in a firm's share of PRI investors (0.0235) enhances environmental performance by 4.79% relative to the sample mean (= 1.9880 × 0.0235 / 0.9757, where 0.9757 is the sample mean of $E\text{-}score\,(normalized)$).

Because we rely on FE estimators in our previous models, we verify the results using a first-difference estimator in model (3). To eliminate unobserved time-invariant heterogeneity across firms in this model, we differentiate FEs out instead of using within transformation.[7] We find that the baseline results remain qualitatively unchanged with $Own.PRI\,investors$ (%) exhibiting statistical significance close to the 5% level ($p = 0.0683$).

To address concerns over the selection of ventures into PRI ownership, we estimate different two-stage approaches in columns (4)-(6). Column (4) estimates the first-stage Heckman correction model (see Equation 4.2) and explains the probability that firm i belongs to the subsample of firms with above-median PRI ownership in year t. We find that, for example, higher funding volumes and a younger firm age attract PRI ownership. We use the predicted individual probabilities to obtain IMRs and calculate GRs (see Section 4.3.5).

Next, we address "selection on observables" and estimate the second-stage Heckman correction model, that is, Equation 4.4. As shown in column (5), the coefficient on $Own.PRI\,investors$ (%) decreases slightly in magnitude (coefficient of 1.860 compared with 1.988 in the baseline model). We also find that the coefficient on IMR is positive and statistically significant at the 5% level (unreported). The results suggest the presence of a minor selection effect that may inflate the coefficient of the baseline model to some extent. Importantly, the causal effect on $E\text{-}score\,(normalized)$ is still statistically significant at the 1% level and economically very relevant. In particular, a one standard deviation increase in a firm's share of investors (0.0235) enhances environmental performance by 4.48% relative to the sample mean (= 1.8599 × 0.0235 / 0.9757, where 0.9757 is the sample mean of $E\text{-}score\,(normalized)$).

Finally, we address "selection on unobservables" by explicitly modelling endogeneity in the error term in column (6). We rerun the baseline model but use GRs (see Equation 4.5) to instrument PRI ownership. We find that $Own.PRI\,investors\,(\%)$ is still positive and statistically significant at the 1% level, which indicates that unobserved heterogeneity does not affect our inferences.

Overall, we conclude that the effect of our baseline model is robust to considerations of both observable and unobservable endogeneity. The findings support H1 and indicate that a higher share of PRI signatories among firms' investors facilitates environmental performance in the funding phase.

4.4.2 Heterogeneity in investors' sustainability preferences

Literature indicates that the commitment of signatories to the PRI varies across investors. In particular, Bauckloh et al. (2021) find that early signatories integrate ESG criteria into their business activities considerably more than late signatories, suggesting heterogeneity among investors in the impact of PRI ownership on environmental performance.

To test whether the effect of PRI signatories on environmental performance varies with respect to the timing of their adoption of the PRI, we construct measures for ownership by early versus late adopters of the PRI. $Own.PRI\,investors\,(\%)^{2015}$ captures ownership by investors that signed the PRI in 2015 or earlier. We also construct corresponding variables for 2013, 2011, and 2009. Next, we rerun the baseline model (see Equation 4.1) but use these modified measures as alternative main explanatory variables. The results are reported in Table 4.4.

Column (1) estimates the effect of $Own.PRI\,investors\,(\%)^{2015}$ on environmental performance. The coefficient increases to 2.430 from 1.988 in the baseline model. A Chow test confirms that investors who signed the PRIs in 2015 or earlier improve environmental performance more than overall PRI ownership, which also includes late signatories (i.e., between 2016 and 2020).

Next, in columns (2)-(4), we lower the threshold for defining early adopters from 2015 to 2013, 2011, and 2009. The coefficients on PRI ownership, all statistically significant at the 1% level, increase to 3.144, 3.076, and 7.795, respectively. Comparing the PRI coefficients across models shows that earlier adoption is generally associated with a greater improvement in environmental performance. Only for the comparison of the 2013 and 2011 thresholds does the Chow test fail to reject the null hypothesis of no significant differences in coefficients. Additionally, the coefficient on $Own.PRI\,investors\,(\%)^{2009}$ in column (4) implies that a one standard deviation increase in early PRI ownership is associated with a 6.22% increase in environmental performance (versus 4.79 % in

Table 4.4
Heterogeneity across investors

This table reports the results of our regressions of startups' environmental performance on ownership by venture capitalists (VCs) that have signed the United Nations Principles for Responsible Investment (PRI), along with the control variables. It reruns the baseline model (see column (2) of Table 4.3) using measures of ownership by early versus late adopters of the PRI as alternative main explanatory variables. Column (1) uses ownership by VCs that signed the PRI in 2015 or earlier. Columns (2)-(4) use the corresponding variables for 2013, 2011, and 2009, respectively. We avoid simultaneity by regressing the contemporaneous dependent variables on the one-year-lagged explanatory variables in all analyses. We perform Chow tests to test for differences in the PRI ownership coefficients. We cluster heteroskedasticity-robust standard errors at the country level. These are reported in parentheses. See Table C1 for definitions of variables.

	(1)	(2)	(3)	(4)
Dependent variable:	E-score (normalized)$_t$			
Own. Early PRI investors (%)$^{2015}_{t-1}$	2.430***			
	(0.379)			
Own. Early PRI investors (%)$^{2013}_{t-1}$		3.144***		
		(0.350)		
Own. Early PRI investors (%)$^{2011}_{t-1}$			3.076***	
			(0.432)	
Own. Early PRI investors (%)$^{2009}_{t-1}$				7.795***
				(0.388)
Funding rounds$_{t-1}$	0.050***	0.049***	0.049***	0.046***
	(0.012)	(0.012)	(0.012)	(0.011)
USD raised (log)$_{t-1}$	-0.001	-0.002	-0.005	-0.010
	(0.033)	(0.032)	(0.033)	(0.031)
Communication intensity (log)$_{t-1}$	0.090***	0.090***	0.090***	0.088***
	(0.012)	(0.012)	(0.012)	(0.012)
Firm age (log)$_{t-1}$	-0.223*	-0.222*	-0.223*	-0.219
	(0.125)	(0.124)	(0.124)	(0.127)
Investor age (Ø, log)$_{t-1}$	0.130***	0.129***	0.130***	0.133***
	(0.019)	(0.019)	(0.019)	(0.020)
Domestic investors (%)$_{t-1}$	0.399**	0.405**	0.359**	0.393**
	(0.134)	(0.134)	(0.141)	(0.140)
Total investors (log)$_{t-1}$	0.074	0.077	0.089	0.088
	(0.094)	(0.092)	(0.097)	(0.092)
Investor funding rounds (Ø, log)$_{t-1}$	0.306***	0.310***	0.302***	0.300***
	(0.024)	(0.023)	(0.029)	(0.029)
Investor portfolio firms (Ø, log)$_{t-1}$	-0.302***	-0.305***	-0.296***	-0.294***
	(0.021)	(0.020)	(0.028)	(0.027)
Year × industry FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Adjusted R-squared	0.593	0.594	0.593	0.594
Observations	887	887	887	887
Differences in coefficients	(1) - bl	(2) - (1)	(3) - (2)	(4) - (3)
Chow-test ($p > \chi^2$)	0.000***	0.000***	0.798	0.000***

the baseline model). Besides the increased economic effect size of early PRI ownership, the presence of early adopters explains firms' environmental performance considerably better than firms' overall share of PRI investors (t-statistics of 20.09 in column (4) vs. 4.94 in the baseline model).

Our results suggest heterogeneity in the impact of PRI investors on environmental portfolio firm performance. Performance improvements seem to be primarily driven by early PRI adopters. Late adopters enhance environmental performance considerably less, indicating potential free-riding behavior.

4.4.3 Heterogeneity across firms

It is also conceivable that the effect of PRI investors on environmental performance varies across firms. We expect a weaker effect for startups that are already highly environmental than for startups that are not. To test this conjecture, we sort all of the environmental scores in our sample into quintiles by industry year. We then construct a dummy variable that takes the value of one if venture i belongs to the top quintile in year $t-1$, and zero otherwise ($High\ e\text{-}score\,(dummy)$). Finally, we rerun the baseline specification (see Equation 4.1), adding an interaction effect between PRI ownership and the dummy variable to the model. The results are shown in column (1) of Table 4.5.

In line with the baseline model, the stand-alone effect of PRI ownership is still positive, with a coefficient of 3.701. Turning to its interaction with the high-environmental performance dummy, we obtain a coefficient of −3.478, which is statistically significant at the 5% level. This suggests that the effect of PRI ownership decreases sharply for firms that are already highly sustainable.

Next, we analyse whether the effect of PRI ownership on corporate environmental performance is stronger among ventures in environmentally sensitive countries. To this aim, we construct two dummy variables indicating whether venture i is headquartered in a country with a strong focus on environmental action or whether it is not headquartered in such a country. We denote these indicators as $Protecting environment(dummy)$ and $Environmental problems(dummy)$, respectively. Country-level environmental sensitivity scores are obtained from the World Values Survey.[8]

In columns (2)-(3), we re-estimate the baseline model, adding the interaction effects between PRI ownership and the dummy variables to the model. Compared with the baseline model, the coefficients on PRI ownership decrease slightly but are still statistically significant at the 1% level. Moreover, we find that both interaction terms are positive and highly statistically significant, indicating that PRI investors play a stronger role in improving the environmental performance of firms in environmentally sensitive countries.

4.4.4 Alternative explanatory variables

We address concerns about endogeneity caused by measurement error in our key explanatory variable. To test whether our inferences are sensitive to the use of $Own.\ PRI\ investors\,(\%)$, we re-

Table 4.5
Heterogeneity across firms

This table reports the results of our regressions of startups' environmental performance on ownership by venture capitalists (VCs) that have signed the United Nations Principles for Responsible Investment (PRI), along with the control variables. It reruns the baseline model (see column (2) of Table 4.3), adding the interaction effects between PRI ownership and different firm characteristics. Column (1) uses a dummy variable that indicates whether venture i's environmental performance belongs to the top quintile in its industry year. Columns (2) and (3) use dummy variables indicating whether venture i is headquartered in a country with a strong focus on environmental action or is not headquartered in such a country. We cluster heteroskedasticity-robust standard errors at the country level. These are reported in parentheses. See Table C1 for definitions of variables.

	(1)	(2)	(3)
Dependent variable:		E-score (normalized)$_t$	
Own. PRI investors (%)$_{t-1}$	3.701***	1.648***	1.669***
	(0.450)	(0.499)	(0.493)
High E-score (dummy)$_{t-1}$	0.587***		
	(0.054)		
Own. PRI investors (%)$_{t-1}$			
× High E-score (dummy)	-3.478**		
	(1.339)		
× Protecting environment (dummy)		3.701***	
		(1.127)	
× Environmental problems (dummy)			2.806***
			(0.751)
Funding rounds$_{t-1}$	0.064***	0.055***	0.056***
	(0.014)	(0.012)	(0.012)
USD raised (log)$_{t-1}$	-0.037	0.002	-0.001
	(0.043)	(0.025)	(0.027)
Communication intensity (log)$_{t-1}$	0.156***	0.091***	0.092***
	(0.008)	(0.012)	(0.010)
Firm age (log)$_{t-1}$	-0.249*	-0.291***	-0.305***
	(0.136)	(0.039)	(0.031)
Investor age (Ø, log)$_{t-1}$	0.131***	0.129***	0.138***
	(0.024)	(0.019)	(0.011)
Domestic investors (%)$_{t-1}$	0.226	0.358***	0.296**
	(0.150)	(0.109)	(0.122)
Total investors (log)$_{t-1}$	-0.019	0.118	0.113
	(0.087)	(0.092)	(0.090)
Investor funding rounds (Ø, log)$_{t-1}$	0.170***	0.317***	0.306***
	(0.042)	(0.028)	(0.036)
Investor portfolio firms (Ø, log)$_{t-1}$	-0.204***	-0.304***	-0.300***
	(0.040)	(0.031)	(0.032)
Year × industry FEs	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes
Adjusted R-squared	0.617	0.610	0.609
Observations	768	877	858

estimate our main model using alternative proxies for environmental VC investment. The results are reported in Table 4.6.

In column (1), we use venture i's number of invested PRI signatories as the alternative main explanatory variable ($Own. PRI\ investors$ (#)). In column (2), we use a dummy variable indicating whether there is at least one PRI signatory among venture i's shareholders ($PRI investor(dummy)$).

Table 4.6
Robustness to alternative explanatory variables

This table reports the results of robustness tests and reruns the baseline model (see column (2) of Table 4.3) using alternative measures of investment by sustainable venture capitalists (VCs). Column (1) uses startup i's number of invested VCs that have signed the United Nations Principles for Responsible Investment (PRI). Model (2) uses a dummy variable indicating whether there is at least one PRI signatory among startup i's shareholders. Column (3) uses the share of environmentally friendly investors over all investors currently engaged in startup i. Column (4) uses the number of environmentally friendly investors engaged in startup i. We cluster heteroskedasticity-robust standard errors at the country level. These are reported in parentheses. See Table C1 for definitions of variables.

	(1)	(2)	(3)	(4)
Dependent variable:	E-score (normalized)$_t$			
Own. PRI investors (#)$_{t-1}$	0.044*			
	(0.016)			
PRI investor (dummy)$_{t-1}$		0.245***		
		(0.038)		
Own. E-friendly investors (%)$_{t-1}$			0.826***	
			(0.092)	
Own. E-friendly investors (#)$_{t-1}$				0.147***
				(0.008)
Funding rounds$_{t-1}$	0.047**	0.039**	0.059***	-0.007
	(0.012)	(0.012)	(0.013)	(0.008)
USD raised (log)$_{t-1}$	0.002	-0.000	-0.038	-0.010
	(0.034)	(0.030)	(0.034)	(0.021)
Communication intensity (log)$_{t-1}$	0.090***	0.090***	0.088***	0.092***
	(0.012)	(0.012)	(0.011)	(0.011)
Firm age (log)$_{t-1}$	-0.233	-0.219	-0.155	-0.210
	(0.125)	(0.126)	(0.127)	(0.133)
Investor age (Ø, log)$_{t-1}$	0.131***	0.130***	0.118***	0.118***
	(0.019)	(0.020)	(0.015)	(0.017)
Domestic investors (%)$_{t-1}$	0.400*	0.414**	0.334	0.350*
	(0.139)	(0.134)	(0.168)	(0.151)
Total investors (log)$_{t-1}$	0.088	0.082	0.094	-0.091
	(0.098)	(0.090)	(0.098)	(0.081)
Investor funding rounds (Ø, log)$_{t-1}$	0.301***	0.306***	0.276***	0.324***
	(0.028)	(0.026)	(0.060)	(0.034)
Investor portfolio firms (Ø, log)$_{t-1}$	-0.292***	-0.304***	-0.261***	-0.364***
	(0.027)	(0.023)	(0.050)	(0.032)
Year × industry FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Adjusted R-squared	0.593	0.593	0.594	0.604
Observations	887	887	887	887

In column (3), we use the share of environmentally friendly investors over all investors currently engaged in venture i ($Own.\,e\text{-}friendly\,investors\,(\%)$). Finally, in column (4), we use the number of environmentally friendly investors engaged in venture i ($Own.\,e\text{-}friendly\,investors\,(\#)$).

We observe positive and statistically significant estimates across all four models, indicating that our main findings are robust to using alternative key explanatory variables. We conclude that endogeneity resulting from errors in the measurement of environmental VC investment is not a concern raised by our findings.

4.4.5 Long-term environmental performance

Finally, we turn to H2, in which we test whether the presence of PRI investors is associated with improved long-term environmental performance in the post-VC financing phase. The results are reported in Table 4.7.

Before we estimate our main model specified in Equation 4.6, we address the possible existence of a selection effect. Column (1) estimates a cross-sectional version of the first-stage Heckman correction model (see Equation 4.2). We use the predicted individual probabilities to obtain IMRs for the selection of ventures into their PRI ownership.

Next, we verify that our baseline results extend to an alternative and more established measure of firms' environmental performance, that is, the TR environmental pillar score. Column (2) estimates the main model specified in Equation 4.6. We regress the TR environmental pillar score for venture i in the year of its IPO t ($Environmental\,pillar$) on PRI ownership and the vector of control variables, both measured in the last year prior to its IPO. We add year FEs to the model to control for unobserved heterogeneity across time. The coefficient on $Own.PRI\,investors\,(\%)$ is positive and statistically significant at the 5% level. Adding the IMR as an additional control variable to the model in column (3) does not affect the results. The results indicate that the presence of PRI investors enhances firms' TR environmental pillar score. It indicates that our baseline inferences extend to an alternative measure of firms' environmental performance.

Finally, we turn to long-term performance. In columns (4), (6), and (8), we rerun the main model but measure venture i's TR environmental pillar score in the years after the IPO, that is, in $t+1$, $t+2$, and $t+3$, respectively. Across all models, we find that PRI ownership has positive effects on long-term environmental performance. Despite the reduced sample sizes, we find that $Own.PRI\,investors\,(\%)$ increases both in magnitude and statistical significance compared with main model (2). This suggests that PRI investors' commitment translates into firms' environmental performance in the years following their IPOs. Adding IMRs to the models in columns (5), (7), and (9) only marginally reduces the coefficients, indicating that selection on observables does not bias our main inferences.

Overall, the results confirm H2 and suggest that sustainability-oriented VC involvement positively affects ventures' environmental performance in the long run.

Table 4.7
Long-term environmental performance

This table reports the results of our cross-sectional regressions of startups' environmental performance on ownership by venture capitalists (VCs) that have signed the United Nations Principles for Responsible Investment (PRI), along with the control variables. Column (1) estimates a cross-sectional version of the first-stage Heckman correction model (see Equation 4.2). Column (2) estimates the main model specified in Equation 4.6. The dependent variable is the Thomson Reuters (TR) environmental pillar score for venture i in the year of its IPO t. Columns (4), (6), and (8) explain venture i's long-term environmental performance. They rerun the main model but measure venture i's TR environmental pillar score in the years after the IPO, that is, in $t+1$, $t+2$, and $t+3$, respectively. Columns (5), (7), and (9) add the inverse Mills ratio to specifications (4), (6), and (8), respectively. We cluster heteroskedasticity-robust standard errors at the country level. These are reported in parentheses. See Table C1 for definitions of variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model:	Selection	Main	IMR	Main	IMR	Main	IMR	Main	IMR
Dependent variable:	$1_t^{\text{many PRI}}$	Environmental pillar$_t$		Environmental pillar$_{t+1}$		Environmental pillar$_{t+2}$		Environmental pillar$_{t+3}$	
Own. PRI investors (%)		0.339**	0.339**	0.360***	0.358***	0.464***	0.463***	0.405***	0.405***
		(0.130)	(0.130)	(0.106)	(0.106)	(0.096)	(0.096)	(0.134)	(0.135)
Funding rounds	-0.072***	0.006***	0.006***	0.002	0.002	0.001	0.001	0.009	0.009
	(0.027)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.009)	(0.009)
USD raised (log)	0.474***	0.004	0.004	0.021**	0.022**	0.015**	0.015**	0.004	0.004
	(0.066)	(0.003)	(0.003)	(0.008)	(0.008)	(0.007)	(0.007)	(0.009)	(0.009)
Communication intensity (log)	0.114***	-0.001*	-0.001*	-0.001	-0.001	0.000	0.000	0.003*	0.003*
	(0.020)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Firm age (log)	-0.102	0.001	0.001	0.020**	0.021**	0.016	0.016	0.004	0.004
	(0.131)	(0.003)	(0.003)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Investor age (Ø, log)	0.484***	-0.000	-0.000	0.003	0.003	0.003	0.003	-0.001	-0.001
	(0.063)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.009)	(0.009)
Domestic investors (%)	-0.899**	-0.006	-0.006	-0.033	-0.034	-0.027	-0.027	-0.055	-0.055
	(0.364)	(0.010)	(0.010)	(0.025)	(0.025)	(0.026)	(0.026)	(0.037)	(0.038)
Total investors (log)	0.814**	-0.012***	-0.012***	-0.023***	-0.024***	-0.021***	-0.021***	-0.009	-0.009
	(0.326)	(0.003)	(0.003)	(0.006)	(0.007)	(0.004)	(0.004)	(0.025)	(0.025)
Investor funding rounds (Ø, log)	0.657***	0.000	0.000	0.001	0.001	0.006	0.007	0.018*	0.018
	(0.099)	(0.002)	(0.002)	(0.006)	(0.006)	(0.009)	(0.009)	(0.010)	(0.011)
Investor portfolio firms (Ø, log)	-0.793***	0.002	0.002	0.005	0.004	-0.003	-0.003	-0.009	-0.009
	(0.177)	(0.001)	(0.001)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	n/a	0.206	0.203	0.181	0.179	0.167	0.163	0.120	0.115
Observations	341	341	341	317	317	257	257	208	208

4.5 Conclusion

This study examines the extent to which sustainable VCs influence the environmental performance of their portfolio firms. Analysing a comprehensive panel dataset of new ventures that went public during the 2010–2022 period, we show that ownership by VC PRI signatories facilitates environmental performance in ventures' funding stages. This finding is robust to considerations of observed and unobserved heterogeneity across firms, industries, and time. The positive effect of PRI ownership on early-stage environmental performance is strongest for ventures (i) that are held to a high extend by early adopters of the PRI, (ii) that have a high upside potential in terms of environmental performance improvement, and (iii) that are located in environmentally sensitive countries. Further analyses confirm that the early impact of sustainable VCs manifests in long-run effects that last up to several years after the portfolio firm's IPO.

Our study highlights the importance of sustainable VC investment for the development of environmental preferences in the early stages of firms' life cycles, shaping their environmental characteristics in the long-run. This has implications for academics, policy-makers, and practitioners. For academics, we offer several opportunities for future entrepreneurship research by demonstrating the empirical validity of the machine learning approach of Mansouri and Momtaz (2022) to assess startups' environmental performance. For policy-makers, our findings shed light on how firms can become sustainable through VC engagement. For practitioners, they identify a novel determinant of environmental performance.

Endnotes

[1] Johnson and Schaltegger (2020) and Anand et al. (2021) provide comprehensive reviews of the recent academic developments in the field of sustainable entrepreneurship research.

[2] See Friede et al. (2015) for a comprehensive literature review.

[3] A few notable exceptions are Vismara (2019), Cumming et al. (2022), and Mansouri and Momtaz (2022).

[4] Research shows that PRI signatories integrate significantly more ESG criteria into their business activities after joining the initiative than non-signatories (Van Duuren et al. (2016), Bauckloh et al. (2021)). Members of the initiative are required to designate responsible employees, provide a management commitment, and establish accountability procedures for the implementation of the six principles of responsible investment. Since 2018, reporting on the implementation of the principles has been mandatory, and failure to meet the relevant criteria over a two-year period results in delisting and termination of membership (UNPRI (2023b)).

[5] Mansouri and Momtaz (2022) provide the Python source code and the technical documentation of their text-based ESG rating on `www.github.com`. They also provide an online interface on `www.sustainableentrepreneurship.org`.

[6] See de Villiers et al. (2022)) for a systematic review of empirical research using TR ESG data.

[7] FE and first-difference models serve the same purpose (i.e., they eliminate unobserved time-invariant heterogeneity), but they rely on different assumptions with regard to the idiosyncratic error term ε_{it}. The FE estimator assumes that the differences in levels, $\varepsilon_{it} - \bar{\varepsilon}_{it}$, are serially uncorrelated; the first-difference estimator assumes serially uncorrelated first-difference errors, $\Delta\varepsilon_{it}$ (Wooldridge (2013)). Because it is not obvious whether the idiosyncratic errors are independent and identically distributed (favoring the FE approach) or follow a random walk (favoring the first-difference estimator), we rely on a first-difference approach for validation.

[8] We base this line of analysis on question *Q111 - Protecting environment vs. Economic growth* and on question *V111 - Environmental problems in the world: Global warming or the greenhouse effect*. We classify *environmentally sensitive* countries as those with an above-median number of positive responses.

Appendix

See next page for Table C1.

Table C1
Definition of main variables

This appendix provides definitions and data sources for the main variables used in the study.

Variable	Definition	Source
Panel A: Environmental performance		
E-score (normalized)	Environmental score at the firm-year level. Constructed by running Mansouri and Momtaz's (2022) machine learning algorithm to text analysis on ventures' Twitter feeds. The score is normalized to the size of the dictionary.	Authors' calculations based on Twitter data
Environmental pillar	Thomson Reuters environmental pillar score at the firm level. The score is composed of three category scores: Resource Use, Emissions, and Environmental Innovation. It reflects a firm's environmental performance and capacity to reduce the use of materials, energy, or water, its commitment to and effectiveness in reducing environmental emissions, and its capacity to create new market opportunities through new environmental technologies or eco-friendly products (Bauckloh et al. (2021)).	Thomson Reuters
Panel B: Key explanatory variables		
Own. PRI investors (%)	The percentage of United Nations PRI signatories among all investors currently engaged in the venture.	Authors' calculations based on Crunchbase and United Nations PRI data
Own. PRI investors (#)	The number of United Nations PRI signatories among all investors currently engaged in the venture.	As above
PRI investor (dummy)	A dummy variable indicating whether at least one United Nations PRI signatory is currently engaged in the venture.	As above
Own. E-friendly investors (%)	The percentage of environmentally friendly investors among all investors currently engaged in the venture. An environmentally friendly investor is an investor whose average E-score (normalized) over all of its portfolio firms is above the median E-score (normalized) of all of the portfolio firms in the sample.	Authors' calculations based on Crunchbase data
Own. E-friendly investors (#)	The number of environmentally friendly investors among all investors currently engaged in the venture.	As above
E-friendly investor (dummy)	A dummy variable indicating whether at least one environmentally friendly investor is currently engaged in the venture.	As above
Panel C: Firm characteristics		
Funding rounds	The cumulative number of all funding rounds conducted by the portfolio firm (Arroyo et al. (2019)).	As above
USD raised (log)	The natural logarithm of one plus the cumulative funding raised by the portfolio firm (in billions of USD) (Block and Sandner (2009), Arroyo et al. (2019)).	As above
Communication intensity (log)	The natural logarithm of one plus the number of total words communicated via a firm's Twitter account (Fisch (2019), Mansouri and Momtaz (2022)).	Authors' calculations based on Twitter data
Firm age (log)	The natural logarithm of one plus the number of years since the portfolio firm was founded. It is often used as a proxy for a firm's establishment in the market (Block and Sandner (2009), Colombo and Grilli (2010), Vismara (2019), Croce et al. (2023)).	Authors' calculations based on Crunchbase data

(*continued*)

Table C1 — *continued*

Variable	Definition	Source
Panel D: Investor characteristics		
Investor age (Ø, log)	The natural logarithm of one plus the average number of years since the investment entity was founded.	Authors' calculations based on Crunchbase data
Domestic investors (%)	The percentage of domestic investors over all investors currently engaged in the venture (Croce et al. (2023)).	As above
Total investors (log)	The natural logarithm of one plus the total number of all investors currently engaged in the venture. It is often used as a proxy for financial success in firms' financing phases (Signori and Vismara (2018), Arroyo et al. (2019), Croce et al. (2023)).	As above
Investor funding rounds (Ø, log)	The natural logarithm of one plus the average number of all previously conducted funding rounds of all investors currently engaged in the venture (Alexy et al. (2012), Arroyo et al. (2019)).	As above
Investor portfolio firms (Ø, log)	The natural logarithm of one plus the average number of portfolio firms held by investors currently engaged in the venture (Croce et al. (2023)).	As above

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Declarations

Pursuant to § 6(4) and § 6(6) of the doctoral degree regulations of the Faculty of Business Administration at the University of Hamburg (PromO 2014), the following sections provide declarations supplemental to the single research projects cumulated in the dissertation. Specifically, declarations include abstracts in German and English language for each research project as well as a listing of publications originated from parts of this dissertation (separately for each chapter). The three key parts of this monograph are Chapters 2 to 4 (see § 6(2b) of PromO 2014). All chapters are based on self-contained research projects.

Project 1:
Team networks and venture success: Evidence from token-financed startups

Abstract (English):

Evidence shows that social network structures drive important economic outcomes. Building on social network theory, this study is the first to analyse the impact of team networks on venture success. Using information about team affiliations for a sample of token-financed startups, we model networks based on team interlocks across firms. Ventures with well-connected teams exhibit higher market valuations and higher token market liquidity. These effects seem to be driven by network-induced information and communication advantages. Specifically, we show that networks matter most when publicly available information is limited. The findings remain robust after controlling for non-team networks and endogeneity.

Abstract (German):

Bisherige wissenschaftliche Erkenntnisse zeigen, dass soziale Netzwerkstrukturen einen wichtigen Einfluss auf wirtschaftliche Ergebnisse haben. Diese Studie ist die erste, welche basierend auf der Theorie sozialer Netzwerke, den Einfluss von Teamnetzwerken auf den Erfolg von Startups untersucht. Wir modellieren Netztwerke zwischen Unternehmen anhand von Informationen über die Teamzugehörigkeit von Startups, die mit digitalen Token finanziert wurden. Unternehmen mit gut

vernetzten Teams weisen höhere Marktbewertungen sowie eine höhere Liquidität auf dem Sekundärmarkt für Token auf. Diese Effekte scheinen durch netzwerkbedingte Informations- und Kommunikationsvorteile beeinflusst zu werden. Insbesondere zeigen wir, dass Netzwerke besonders relevant sind, wenn die öffentliche Verfügbarkeit von Informationen begrenzt ist. Die Ergebnisse behalten auch nach einer Kontrolle von Nicht-Team-Netzwerken und weiteren Endogenitätskontrollen ihre Gültigkeit.

Publication Status of the Project:

Except for minor changes, the version documented in Chapter 2 of this dissertation has been submitted to *The Journal of Business Venturing*. The Thomson Reuters JCR Impact Factor of this journal is 13.139 (May 2023). The VHB (German Academic Association for Business Research) Journal Ranking JOURQUAL3 ranks this periodical "A".

Self-Declaration of Personal Contribution (PromO §6(2b) and §6(4)):

Co-authors of this article are Wolfgang Drobetz (University of Hamburg), and Henning Schröder (University of Flensburg). My personal contributions to this research project involve in particular the design of the conceptual and empirical framework, the data management and the execution of the statistical analyses using Stata and Python, the economic interpretation of the empirical results, as well as the preparation of the manuscript.

Project 2:

Venture capital investor heterogeneity and funding success

Abstract (English):

This study examines the relationship between investor heterogeneity and VC funding success. Specifically, we analyse how heterogeneity among VC investors affects the post-seed funding success of startups. Our results indicate that cultural disparities among individual investors significantly decrease the probability of obtaining VC funding in subsequent rounds, and also negatively impact the amount of future VC funding raised. Our results remain robust to alternative measures of

investor heterogeneity and controls for endogeneity concerns common to entrepreneurial finance studies. Our sample consists of nearly 19,000 US-based startups seeking VC funding from 2010 to 2022. Overall, our analysis deepens our understanding of how diverse ownership affects firm success in the entrepreneurial context.

Abstract (German):

Diese Studie untersucht den Zusammenhang zwischen der Heterogenität von Investoren und dem unternehmerischen Erfolg im Rahmen von Venture Capital (VC)-Finanzierungen. Konkret analysieren wir, wie Heterogenität unter VC-Investoren den Finanzierungserfolg von Startups in zukünftigen Finanzierungsrunden beeinflusst. Wir zeigen, dass die kulturelle Distanz zwischen einzelnen Investoren die Wahrscheinlichkeit einer zukünftigen VC-Finanzierung signifikant reduziert. Darüber hinaus zeigen wir, dass die Heterogenität der Investoren auch negativ mit der Höhe des zukünftig eingeworbenen Risikokapitals zusammenhängt. Unsere Ergebnisse bleiben auch dann gültig, wenn alternative Heterogenitätsmaße herangezogen werden und für Endogenitätsprobleme, die üblicherweise in Studien zur Unternehmensfinanzierung auftreten, kontrolliert wird. Unsere Stichprobe besteht aus fast 19.000 in den USA ansässigen Startups, die zwischen 2010 und 2022 Risikokapital aufgenommen haben. Insgesamt vertiefen die Ergebnisse dieser Studie das Verständnis der Auswirkungen von diversen Eigentümerstrukturen im unternehmerischen Kontext.

Publication Status of the Project:

The version documented in Chapter 3 of this dissertation has working paper status.

Self-Declaration of Personal Contribution (PromO §6(2b) and §6(4)):

This article is single-authored. My personal contributions to this research project involve the development of the conceptual framework and the empirical research design as well as the execution of all empirical analyses and the preparation of the manuscript.

Project 3:
On the impact of sustainable venture capital

Abstract (English):

Investment by venture capitalists (VCs) that have signed the United Nations Principles for Responsible Investment (PRI) positively affects startups' environmental performance. Our findings are based on a comprehensive sample of new ventures that went public during the 2010–2022 period. To capture startups' environmental properties in the funding phase, we adapt the machine learning approach of Mansouri and Momtaz (2022). Late adopters of the PRI enhance environmental performance significantly less than early adopters, indicating potential free-riding behavior. Additional analysis reveals that the impact of PRI ownership on environmental performance is weaker for ventures that are already highly sustainable and stronger for ventures in environmentally sensitive countries. Finally, we find that exposure to PRI VCs during the funding stage shapes startups' long-term environmental performance.

Abstract (German):

Investitionen von Risikokapitalinvestoren (VCs), welche die UN Principles for Responsible Investment (PRI) unterzeichnet haben, wirken sich positiv auf die Umweltleistung von Startups aus. Unsere Ergebnisse basieren auf einer umfassenden Stichprobe von Startups, die zwischen 2010 und 2022 an einer Börse gelistet wurden. Um die Umwelteigenschaften von Startups in der Finanzierungsphase zu erfassen, verwenden wir eine Methode des maschinellen Lernens von Mansouri and Momtaz (2022). Späte Unterzeichner der PRI verbessern in ihrer Rolle als Investoren die Umweltleistung signifikant weniger als frühe Unterzeichner. Dies deutet auf ein potentielles Trittbrettfahrerverhalten hin. Weitere Analysen zeigen, dass der Einfluss von PRI-Investoren auf die Umweltperformance bei Unternehmen, die bereits sehr nachhaltig agieren, schwächer und bei Unternehmen aus Ländern mit einer hohen Sensibilität für Umweltaspekte stärker ist. Schließlich stellen wir fest, dass das Engagement von PRI-Investoren während der Finanzierungsphase die Umweltleistung von Startups langfristig beeinflusst.

Publication Status of the Project:

The version documented in Chapter 4 of this dissertation has working paper status.

Self-Declaration of Personal Contribution (PromO §6(2b) and §6(4)):

Co-authors of this article are Marwin Mönkemeyer (University of Hamburg) and Henning Schröder (University of Flensburg). My personal contributions to this research project involve in particular the design of the conceptual and empirical framework, the data management and the execution of the statistical analyses using Stata, the economic interpretation of the empirical results, as well as the preparation of the manuscript. Marwin Mönkemeyer provided a specific Python program code which allows us to evaluate the environmental performance of ventures using textual analysis.

Affidavit

Ich, Kathrin Rennertseder, versichere an Eides statt, dass ich die Dissertationsschrift mit dem Titel

„Essays in Entrepreneurial Finance"

selbst und im Falle einer Zusammenarbeit mit anderen Wissenschaftlern gemäß den beigefügten Darlegungen nach §6 (4) der geltenden Promotionsordnung der Fakultät für Betriebswirtschaft der Universität Hamburg in der Ausführung vom 09. Juli 2014 verfasst habe. Andere als die angegebenen Hilfsmittel habe ich nicht verwendet. Die den herangezogenen Werken wörtlich oder sinngemäß entnommenen Stellen sind als solche gekennzeichnet. Darüber hinaus versichere ich, keine kommerzielle Promotionsberatung in Anspruch genommen zu haben. Die vorliegende Dissertation wurde in keinem früheren Promotionsverfahren angenommen oder als ungenügend beurteilt.

Hamburg, den 19. Mai 2023

Kathrin Rennertseder