Empirical Essays on Agency Problems in Venture Capital

Dissertation to obtain the doctoral degree of
Economic Sciences (Dr. oec.)

Faculty of Business, Economics and Social Sciences

University of Hohenheim

Institute for Financial Management

submitted by
Lukas König

from Ludwigsburg

2023

Day of Disputation:	September 07, 2023
Faculty Dean:	Prof. Dr. Jörg Schiller
Supervisor:	Prof. Dr. Hans-Peter Burghof
Second Reviewer:	Prof. Dr. Dirk Hachmeister

Acknowledgement

First and foremost, I am more than grateful for the provided opportunities by and the support of my doctorate supervisor Prof. Dr. Hans-Peter Burghof. I am especially grateful for the great freedom he gave me in working out my doctorate, which allowed me to keep working full-time in a demanding job while at the same time progressing on my research projects. Looking back, it seems quite unlikely that I would have been able to finish this PhD project with anyone else as my supervisor.

Next, I want to thank everybody at the Chair of Banking and Financial Services. Juggling my research, job, newly founded family, and other private projects did not leave me with enough time to be involved in the everyday Chair business. Nevertheless, I always felt like part of the team.

I also want to thank Ibrahim Yazgan who became a good friend while working together at Mercedes. His persistent nature and relentless pursuit to find out how far we can push it gave me the required confidence that pursuing a doctorate is the right step for me to take.

Finally, I could not have undertaken this journey without my family. Nadja – thank you for your understanding and unwavering support. Mats – knowing you would soon join our family gave me the pressure I needed to finish this thesis with laser focus.

Abstract

This thesis aims to contribute to the existing research on agency problems in the venture capital industry. It consists of three empirical essays. The venture capital investment process involves various parties with potentially conflicting interests who enter long-term contracts under incomplete information. Namely, these parties are the venture capital firm, led by general partners usually referred to as venture capitalists who manage the funds; the entrepreneurs seeking funding for their venture; and the limited partners who provide the capital for the venture capital funds to invest. The relationship between the three parties is complex, as the general partner serves both as an agent for the limited partner and a principal for the entrepreneur. While all parties may have the common goal of successful investments, they may also have conflicting interests that can lead to tension in the relationship. Each of the included essays examines one selected aspect related to agency theory in venture capital.

In the first essay, we explore the potential agency conflict between limited partners and general partners in venture capital firms due to changes in investment style. Investment style refers to the characteristics of a venture capital fund's portfolio, such as the portfolio companies' stage of development, location, and industry. While investment style can significantly impact the risk and return profile of a fund, it is usually not explicitly agreed upon by limited and general partners. We argue that changes in investment style, known as style drifts, can reveal information about the risk-taking behavior of venture capitalists and present empirical evidence in support of this claim. To determine whether style drifts constitute an agency conflict, we consider two sets of hypotheses. The first set posits that style drifts are intentional decisions to take on more risk, potentially driven by incentives related to compensation or employment. The second set suggests that style drifts may occur because of competitive pressure and may not necessarily be indicative of an intent to increase risk. Our findings suggest that style drifts are likely to create an agency conflict, as the evidence supports the hypothesis that well-performing venture capitalists increase investment risk to benefit from higher compensation potential via carried interest when they feel confident, they will be able to raise a follow-on fund securing their base income via management fees. Additionally, we examine the impact of style drifts on individual investments and fund performance and find that overall, style drifts hurt a fund's exit rate, indicating the potential for increased risk.

In the second essay, we examine the relationship between venture capitalists and entrepreneurs, specifically focusing on the role of information asymmetry in the funding process. Using text classification and text mining techniques we analyze the content and level of detail in capital allocation plans provided by entrepreneurs to investors, which serve as a proxy for private informational updates that are typically not widely available. Our analysis shows that investors do consider the content and specificity of these updates when making valuation decisions and that both positive information signals and more detailed information are related to higher valuations. We also investigate the effect of the relative level of information asymmetry between venture capitalists and entrepreneurs on the value of these updates, finding that they are more impactful in situations where there is a higher level of information asymmetry. The results of our study have practical implications for entrepreneurs, as we find that the negative impact of negative information signals can be offset by providing highly specific information and that the value of an informational update is influenced by the existing level of information asymmetry.

In the third essay, I explore the impact of university affiliations on the initial matching process between venture capitalists and founders, the involvement of the investor during the funding relationship, and the eventual startup performance and investment exit success. University affiliations can influence the funding relationship through two channels: first, attending a top university may serve as a signal of founder quality to venture capitalists, helping them to avoid adverse selection; second, shared alumni networks may establish trust and reduce information asymmetry between otherwise unknown individuals. Using a dataset of 42,101 investments involving 38,452 unique venture capitalists and founders, I find that educational ties between venture capitalists and founders have a positive effect on the funding relationship, including the initial matching, the level of involvement of the investor during the funding relationship, and the eventual startup performance and investment exit success. The effect of sharing an educational background between a venture capitalist and a founder is about five times larger than the effect of a founder attending a top university. Further, the results also show that educational ties are more valuable the more exclusive they are, and that redundant ties between the founding team and the investors have diminishing value for the investment decision.

Kurzzusammenfassung

Die vorliegende Arbeit soll einen Beitrag zur bestehenden Forschung über Agency-Probleme in der Risikokapitalbranche leisten. Sie besteht aus drei empirischen Aufsätzen. Am Prozess der Risikokapitalinvestitionen sind verschiedene Parteien mit potenziell gegensätzlichen Interessen beteiligt, die unter unvollständigen Informationen langfristige Verträge abschließen. Bei diesen Parteien handelt es sich um die Risikokapitalgesellschaft unter der Leitung von Risikokapitalgebern, die die Fonds verwalten, um die Unternehmer, die eine Finanzierung für ihr Unternehmen suchen, und um die Limited Partners, die das Kapital für die Investitionen der Risikokapitalfonds bereitstellen. Die Beziehung zwischen den drei Parteien ist komplex, da der Risikokapitalgeber sowohl als Agent für den Limited Partners als auch als Prinzipal für den Unternehmer fungiert. Auch wenn alle Parteien das gemeinsame Ziel erfolgreicher Investitionen verfolgen, können sie auch gegensätzliche Interessen haben, die zu Spannungen in der Beziehung führen können. Jeder der enthaltenen Aufsätze untersucht einen ausgewählten Aspekt im Zusammenhang mit der Agency-Theorie bei Risikokapital.

Im ersten Aufsatz wird der potenzielle Agency-Konflikt zwischen Limited Partners und Risikokapitalgebern in Risikokapitalgesellschaften aufgrund von Änderungen des Investitionsstils untersucht. Der Investitionsstil bezieht sich auf die Merkmale des Portfolios eines Risikokapitalfonds, wie z.B. das Entwicklungsstadium, den Standort und die Branche der Portfoliounternehmen. Der Anlagestil kann sich zwar erheblich auf das Risiko- und Ertragsprofil eines Fonds auswirken, wird aber in der Regel nicht ausdrücklich von den Limited Partners und Risikokapitalgebern vereinbart. Wir argumentieren, dass Veränderungen im Anlagestil, die so genannten Style Drifts, Aufschluss über das Risikoverhalten von Risikokapitalgebern geben können, und präsentieren empirische Belege zur Unterstützung dieser Behauptung. Um festzustellen, ob Style Drifts einen Agency-Konflikt darstellen, prüfen wir zwei Hypothesen. Die erste Hypothese besagt, dass Style Drifts absichtliche Entscheidungen zur Übernahme von mehr Risiko sind, die möglicherweise durch Anreize im Zusammenhang mit der Vergütung bedingt sind. Die zweite Hypothese besagt, dass Style Drifts als Folge von Wettbewerbsdruck auftreten können und nicht unbedingt auf eine beabsichtigte Risikoerhöhung hindeuten. Unsere Ergebnisse deuten darauf hin, dass Style Drifts wahrscheinlich zu einem Agency-Konflikt

führen, da die Ergebnisse die Hypothese stützen, dass leistungsstarke Risikokapitalgeber das Anlagerisiko erhöhen, um von einem höheren Vergütungspotenzial über Carried Interest zu profitieren, wenn sie sich sicher sind, dass sie in der Lage sein werden, einen Folgefonds einzuwerben, der ihr Grundeinkommen über Managementgebühren sichert. Darüber hinaus untersuchen wir die Auswirkungen von Style Drifts auf einzelne Investitionen und die Fondsperformance und stellen fest, dass Style Drifts insgesamt die Erfolgsquote eines Fonds beeinträchtigen, was auf ein erhöhtes Risiko hinweist.

Im zweiten Aufsatz untersuchen wir die Beziehung zwischen Risikokapitalgebern und Unternehmern und konzentrieren uns dabei insbesondere auf die Rolle der Informationsasymmetrie im Finanzierungsprozess. Mithilfe von Textklassifizierungs- und Textmining-Techniken analysieren wir den Inhalt und den Detaillierungsgrad von Kapitalallokationsplänen, die den Investoren von den Unternehmern zur Verfügung gestellt werden. Unsere Analyse zeigt, dass Investoren den Inhalt und die Spezifität dieser Informationsaktualisierungen bei ihren Bewertungsentscheidungen berücksichtigen und dass sowohl positive Informationssignale als auch detailliertere Informationen mit höheren Bewertungen verbunden sind. Wir untersuchen auch die Auswirkungen des relativen Ausmaßes der Informationsasymmetrie zwischen Risikokapitalgebern und Unternehmern auf den Wert dieser Informationsaktualisierungen und stellen fest, dass sie in Situationen mit einem höheren Maß an Informationsasymmetrie größere Auswirkungen haben. Die Ergebnisse unserer Studie haben praktische Auswirkungen für Unternehmer, da wir feststellen, dass die negativen Auswirkungen negativer Informationssignale durch die Bereitstellung hochspezifischer Informationen ausgeglichen werden können und dass der Wert einer Informationsaktualisierung vom bestehenden Grad der Informationsasymmetrie beeinflusst wird.

Im dritten Aufsatz untersuche ich die Auswirkungen von Universitätszugehörigkeiten auf den anfänglichen Matching-Prozess zwischen Risikokapitalgebern und Gründern, die Beteiligung des Investors während der Finanzierungsbeziehung und die letztendliche Performance des Start-ups und den Erfolg der Investition beim Ausstieg. Die Zugehörigkeit zu einer Universität kann die Finanzierungsbeziehung über zwei Kanäle beeinflussen: Erstens kann der Besuch einer Spitzenuniversität den Risikokapitalgebern als Signal für die Qualität des Gründers dienen und ihnen helfen, ‚Adverse Selection' zu vermeiden; zweitens können gemeinsame Alumni-Netzwerke Vertrauen schaffen und Informationsasymmetrien zwischen ansonsten unbekannten Personen verringern. Anhand eines Datensatzes von 42.101 Investitionen, an denen 38.452 Risikokapitalgeber und Gründer beteiligt waren, stelle ich fest, dass sich Bildungsbeziehungen zwischen Risikokapitalgebern und Gründern positiv auf die Finanzierungsbeziehung auswirken, einschließlich des anfänglichen Matchings, des Umfangs des Engagements des Investors während der Finanzierungsbeziehung und der letztendlichen Startup-Performance und des Erfolgs beim Ausstieg aus der Investition. Der Effekt eines gemeinsamen Bildungshintergrunds zwischen einem Risikokapitalgeber und einem Gründer ist etwa fünfmal so groß wie der Effekt eines Gründers, der eine Spitzenuniversität besucht hat. Außerdem zeigen die Ergebnisse, dass Bildungsbeziehungen umso wertvoller sind, je exklusiver sie sind, und dass redundante Beziehungen zwischen dem Gründerteam und den Investoren einen abnehmenden Wert für die Investitionsentscheidung haben.

Contents

1 Introduction **1**

1.1 Motivation . . . 1

1.2 Structure of the Thesis . . . 3

2 Essay 1 – The Investment Style Drift Puzzle and Risk-Taking in Venture Capital **7**

2.1 Introduction . . . 8

2.2 Background and Hypotheses . . . 10

2.2.1 Style Drifts and Risk-Taking . . . 10

2.2.2 Style Drift in the Private Equity Literature . . . 13

2.2.3 Motivation for and Performance Implications of Style Drifts . . . 14

2.3 Data . . . 19

2.3.1 Sample and Variable Definitions . . . 19

2.3.2 Sample Description . . . 26

2.4 Econometric Analysis . . . 34

2.4.1 What is driving Style Drifts? . . . 34

2.4.2 What are the Performance Implications of Investment Style Drifts? 46

2.5 Conclusion . . . 54

3 Essay 2 – Tell Me Something New: Startup Valuations, Information Asymmetry, and the Mitigating Effect of Informational Updates **57**

3.1 Introduction . . . 58

3.2 Informational Updates in Venture Capital . . . 59

3.2.1 Information Signals and Information Asymmetries . . . 59

3.2.2 Information Specificity . . . 61

3.2.3 Level of Information Asymmetry . . . 62

3.3 Data and Methodology . . . 63

3.3.1 Sample Construction . . . 63

3.3.2 Text Analysis Methodology . . . 64

3.3.3 Variables Construction . . . 68

3.3.4 Sample Overview and Descriptive Statistics 70
3.4 Empirical Analysis and Discussion 72
3.4.1 Main Econometric Approach 72
3.4.2 Empirical Results 73
3.4.3 Robustness of Results and Limitations 79
3.5 Conclusion 80

4 Essay 3 – Cut from the same Cloth: The Role of University Affiliations in Venture Capital Investments 83
4.1 Introduction 84
4.2 Background, Related Literature, and Hypotheses 86
4.3 Data and Variables 90
4.3.1 Sample Construction and Data Collection 90
4.3.2 University Affiliations of Individuals Involved in Investments 93
4.3.3 Counterfactual Investment Approach 98
4.3.4 Other Variables 99
4.4 Empirical Results and Discussion 103
4.4.1 Investment Decision 103
4.4.2 Scope of the Funding Relationship 113
4.4.3 Riskiness of the Investment 117
4.4.4 Investment Success 121
4.4.5 Limitations 124
4.5 Conclusion 126

5 Conclusion 129

Bibliography 133

A Appendix xiii
A.1 Declarations of Co-Authorship xiv
A.2 Curriculum Vitae xvi
A.3 Eidesstattliche Versicherung xviii

1 Introduction

> *Venture capital is about extracting enormous signal out of very little data.*
>
> — **Nigel Morris**
> (Venture Capitalist)

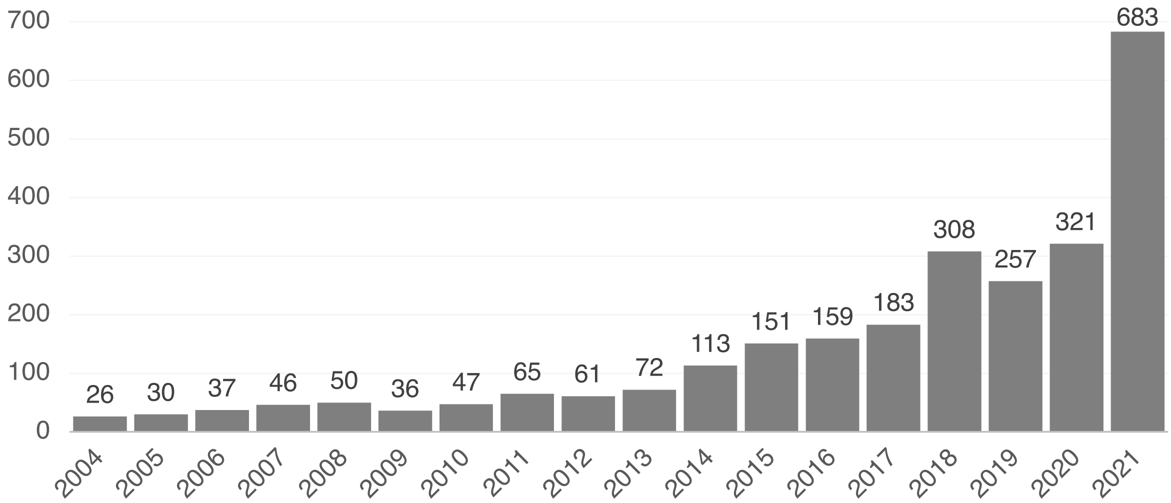
1.1 Motivation

The most common organizational form of venture capital financing is the independent private partnership between limited partners and general partners organized in venture capital firms. The interplay of general partners, limited partners, and entrepreneurs on a very simplified level works as follows: venture capital firms act as financial intermediaries that raise funds from investors (e.g. pension funds or family offices) acting as limited partners. General partners at the venture capital firm usually contribute a small fraction[1] of the fund's capital as well to ensure *'skin in the game'*, i.e. align interests between limited and general partners. Eventually, general partners invest the fund's total capital into entrepreneurial companies on behalf of their limited partners. The goal of the fund is to increase the value of the invested capital over the fund's lifetime. This is achieved by exiting its portfolio companies after – in the best case – considerably increasing their value.

Since the 1990s, the venture capital industry has experienced significant growth and evolution. In the early 1990s, the total amount of venture capital invested in the United States was around USD $6 billion per year, accounting for almost 100% of global venture capital investments (NVCA 2011). Since then, venture capital has become an increasingly important factor for innovation financing and economic growth globally. Figure 1.1 depicts the development of global aggregate venture capital funding over the last two decades. By 2010, global aggregate venture capital funding had increased to around $47 billion. In 2021 venture-capital-backed companies in the United States raised almost $335 billion, while globally venture capital-backed companies raised around $683 billion (NVCA 2022), underscoring the field's growing importance both in the

[1] Typically general partners provide approximately 1% of the fund's capital (Sahlman 1990).

Figure 1.1.: Global Venture Capital Investment into Portfolio Companies (2004-2021)



Source: NVCA (2022); all figures in billion USD

United States and the rest of the world. Today, it is a crucial source of funding for entrepreneurial ventures, providing the capital and expertise needed to turn innovative ideas into successful businesses. The development naturally has led to an increased interest among academics, policy-makers, regulators, and practitioners in the subject (Cumming and Vismara 2017). A growing body of literature has scrutinized various aspects of venture capital. The most active research areas include, e.g. the relationship between funds and companies, heterogeneity among venture capital investors, the process of matching between venture capitalists and entrepreneurs, or the effect of venture capital on the macroeconomic development.[2]

From a theoretical perspective, the overall venture capital investment process involves several entities and agents with diverging interests that have to enter incomplete contracts with time horizons of several years (see e.g. Hart 1995). This includes the venture capital firm in which venture capitalists acting as general partners organize funds, the entrepreneurs seeking funding, and the limited partners providing the capital for the venture capital firm to invest. Figure 1.2 provides a schematic and simplified overview of a typical venture capital setup. Sahlman (1990) describes and analyzes the relationship between the three parties. What makes the venture capital context especially interesting from an agency theory perspective is that a general partner acts both as an agent (for the limited partner) and as a principal (for the entrepreneur). While all three parties may share the common goal of achieving successful investment outcomes, they may also have conflicting interests that can lead to tension in venture capital relationships. For example,

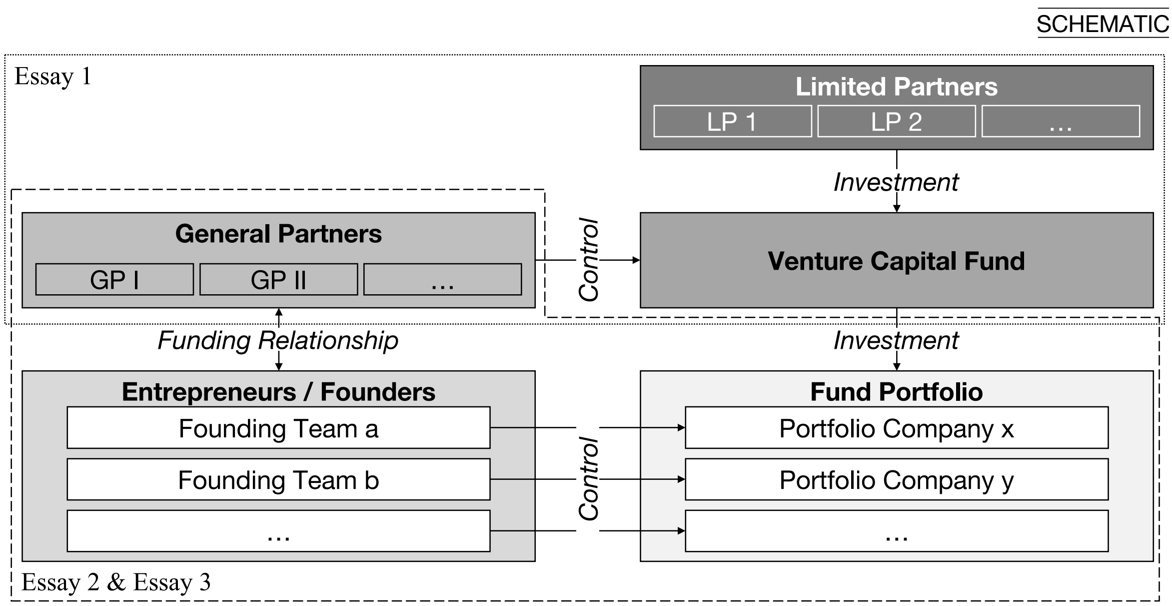
[2]See e.g. Tykvová (2018b) or Rin et al. (2013) for a structured survey of literature in the field.

the general partner may want to closely monitor and control the company's operations to ensure that the investment is being used effectively, while the entrepreneur may resist this level of oversight. Or, the limited partner might desire a different risk-return profile for the fund than the general partner who might be maximizing his own compensation via risky investments. These examples can all be related to typical situations in agency theory: moral hazard and information asymmetry, adverse selection, and signalling. This thesis builds on the theoretical framework provided by contract and agency theory and contributes to empirical research in venture capital.

1.2 Structure of the Thesis

This thesis seeks to contribute to the literature about agency issues in venture capital. It consists of three empirical essays connecting aspects of venture capital financing to agency theory. Figure 1.2 gives a simplified overview of the relevant venture capital setup and schematically highlights each essay's context and which relationship they scrutinize.

Figure 1.2.: Graphical Structure of this Thesis



The first essay included in this dissertation (presented in chapter 2) sheds light on a potential agency conflict between limited partners and general partners. *The Investment Style Drift Puzzle and Risk-Taking in Venture Capital* is co-authored with Hans-Peter Burghof. The main idea comes from Lukas König, who also conducted most work on the project. The essay is published in the *Review of Corporate Finance*[3]. It examines the phenomenon of investment style drifts in venture capital. Investment style in the context of venture capital refers to the development stage, location, and industry of the portfolio companies in a venture capital fund's portfolio. Usually, investment style is not contractually agreed on between limited partners and general partners, even though it majorly influences the risk-return profile of a fund. Thus, if general partners decide to adapt their investment style, the limited partners cannot influence that decision and must trust them to act in their best interests. In the essay, we argue that style drifts carry information about the risk-taking of venture capitalists and provide empirical evidence for that notion. To find out whether deviations from an expected investment style constitute an agency conflict, the essay analyzes the motivational factors for style drifts by differentiating two groups of hypotheses. The first group assumes style drifts to be deliberate risk-taking decisions. We apply the concepts of compensation incentives and employment incentives established as tournament effect in the mutual fund literature to venture capital funds. If general partners increase the fund's risk profile to maximize their own carried interest potential, this might not be in the best interest of limited partners. The second group of hypotheses explains style drifts with competitive pressure. If general partners adapt their style due to necessity the resulting risk implications might simply be side effects, which could still be in the best interest of limited partners. The empirical results provide evidence for the first group of hypotheses, i.e. that style drifts constitute an agency conflict. Results show that general partners adapt their investment style to exploit their incentive structure by playing off their compensation and employment incentives against each other. Further, both deal-level, as well as fund-level analyses, show that style drifts have a negative effect on exit performance even after controlling for endogeneity concerns.

The second essay in this dissertation is titled *Tell Me Something New: Startup Valuations, Information Asymmetry, and the Mitigating Effect of Informational Updates* (presented in chapter 3). It is co-authored with Julius Tennert who provided the original idea and data. Lukas König conducted all conceptual and empirical work on the project. The essay is published in *Venture Capital*[4]. The essay focuses on the principal-agent relationship between venture capitalists and entrepreneurs. The primary objectives of this paper are to contribute to the literature on the significance of information asymmetry in the context of venture capital funding relationships and to examine the mitigative

[3]Lukas Koenig and Hans-Peter Burghof (2022). "The Investment Style Drift Puzzle and Risk-Taking in Venture Capital". In: *Review of Corporate Finance* 2.3, pp. 527–585. DOI: 10.1561/114.00000023

[4]Lukas Koenig and Julius Tennert (2022). "Tell me something new: startup valuations, information asymmetry, and the mitigating effect of informational updates". In: *Venture Capital* 24.1, pp. 47–69. DOI: 10.1080/13691066.2022.2026744

effects of informational updates on the funding process. Information asymmetry is a key problem for venture capitalists acting as outside investors who are at an informational disadvantage compared to the founders of the entrepreneurial ventures in which they invest. We use text classification and text mining approaches to extract the content and specificity of capital allocation plans in a unique sample of 1,550 European funding rounds. This serves as a proxy for the private informational updates shared with investors by entrepreneurs that are usually not widely available to researchers. We hypothesize that informational updates that signal that an entrepreneurial venture is in a later stage of development, i.e. closer to positive cash flows, or that provide more specific information about the venture's prospects are related to higher valuations. We provide empirical evidence that investors in fact do consider the content and specificity of the provided informational updates in their valuation decisions. Both positive information signals and more specific information are related to higher valuations. The paper also hypothesizes that the relative level of information asymmetry between venture capitalists and entrepreneurs will affect the impact of informational updates, with updates being less impactful in situations where there is already a low level of information asymmetry. The results support the hypotheses, showing that the value of informational updates is higher in situations with higher levels of information asymmetry.

The third essay in this dissertation (presented in chapter 4) focuses on the initial matching between venture capitalists and the founding team. The essay titled *Cut from the same Cloth: The Role of University Affiliations in Venture Capital Investments* is single authored by Lukas König. At the time of writing this dissertation, it had a "revise and resubmit" at the *Journal of Corporate Finance*[5]. The initial two-sided matching between a venture capitalist and a founder is the most important decision for both parties in the overall funding relationship. Selecting the wrong startup or venture capitalist can have a negative impact for the counterparty. Venture capitalists might end up with low-quality companies in their portfolio and founders might have to give up parts of their decision power to someone not aligned with their interests. In this paper, I exploit a unique data set comprising 42,101 investments involving 38,452 unique venture capitalists and founders to shed light on how their university affiliations might mitigate issues related to adverse selection and information asymmetries. There are two channels where university affiliations might impact a funding relationship. First, top-university affiliations can act as a founder-quality signal for venture capitalists helping them to avoid adverse selection, and second, belonging to the same alumni network might establish generalized trust between otherwise unknown individuals reducing information asymmetry between

[5]Lukas Koenig (2022). "Cut from the same Cloth: The Role of University Affiliations in Venture Capital Investments". Working Paper available at SSRN. DOI: 10.2139/ssrn.4248420

them. Results show that the effect of sharing an educational background is about five times larger than the effect of a founder attending a top university. More precisely, an educational tie between a venture capitalist and a founder increases the likelihood of a match by 23.6% over the unconditional baseline probability. Further, results also show that educational ties influence the whole lifecycle of the funding relationships even after the initial investment decision. In the presence of an educational tie venture capitalists are more likely to invest in younger more risky companies, take board seats, and lead the investment syndicate. Finally, the results indicate that a shared educational background is related to a higher likelihood of a successful exit.

2

Essay 1 – The Investment Style Drift Puzzle and Risk-Taking in Venture Capital

Abstract

Limited partners allocate capital into venture capital funds with the expectation of a risk-return profile matching the fund's investment style in terms of startup investment stage, location, and industry. This paper draws a connection between style drifts in these three dimensions and the connected risk-taking attitude of the general partner. By analyzing a sample of 31,521 investments concerning the motivation for style drifts, this paper seeks to answer whether style drifts are deliberate risk shifts or happen out of competitive pressure. The results suggest that venture capitalists increase risk when they have strong past performance and public markets are bullish to make the most of the balance of compensation and employment incentives. This balancing most likely constitutes an agency conflict between limited partners and general partners. Further, results show that riskier style drifts have a negative impact on investment performance even after controlling for performance persistence and endogeneity. Finally, the findings show that aggregate style drift has a negative effect on a fund's performance measured as its exit rate.

Keywords: investment style, style drifts, agency conflict, risk, venture capital, entrepreneurial finance

Bibliographic Information

Lukas Koenig and Hans-Peter Burghof (2022). "The Investment Style Drift Puzzle and Risk-Taking in Venture Capital". In: *Review of Corporate Finance* 2.3, pp. 527–585. DOI: 10.1561/114.00000023

2.1 Introduction

The most common organizational form of venture capital is the independent private partnership between limited partners (LPs) providing capital and general partners (GPs) managing this capital in venture capital funds. The interplay of the different actors involved in venture capital on a very simplified level works as follows: venture capital firms are financial intermediaries that raise funds from investors (e.g. pension funds or family offices) acting as LPs. GPs in the form of the venture capital firm usually contribute a small fraction to the fund's capital as well and invest the fund's total capital into entrepreneurial companies on behalf of their LPs. The compensation of GPs consists of a fixed management fee based on assets under management and the option-like carried interest - a share of the fund's proceeds. The goal of the fund is to increase the value of the invested capital over the fund's lifetime. This is achieved by exiting its portfolio companies after (in the best case) considerably increasing their value before redistributing the fund's capital to the investors. Cumming et al. (2009) and Buzzacchi et al. (2015) both report that a large fraction of LPs sees investment style drifts as one of their major concerns as reported in industry surveys. It is therefore puzzling that the overall investment style is usually not contractually guaranteed between GP and LP. An implicit agreement about investment style is consequently the only indication of the expected risk-return profile of a fund for the LP. In other words, LPs select funds to realize a desired risk-return allocation for their own portfolio based on the fund's expected investment style. The investment style of a fund in its core is made up of the development stage, the location, and the industry of the entrepreneurial ventures in its portfolio. As LPs have no influence on the investment decisions after their initial capital commitment and therefore have to trust the GPs to act in their best interest, LPs and GPs form a classical principal-agent relationship. When GPs drift from their originally expected investment style, LPs cannot usually withdraw capital to rebalance the risk-return profile of their own portfolio. Thus, this opens up a potential agency conflict.

This paper seeks to contribute to the literature in several ways. First, the paper builds on the findings of prior work in the field of investment style drifts in venture capital adding further style dimensions and a new theoretical framework to the analysis. While there is extant research about investment style in mutual funds (e.g. Chan et al. 2002; Barberis and Shleifer 2003; K. C. Brown et al. 2009; Wermers 2012), there is only a very small niche of research (Cumming et al. 2009; Buzzacchi et al. 2015; Bubna et al. 2020) on the topic in private equity mostly focussing on stage drifts, even though style drifts, in general, appear to be a rather common phenomenon there as well. Second, by focussing on risk-taking implications of style drifts, the paper adds to the growing literature about agency conflicts between LPs and GPs in private equity (Jenkinson et al. 2013; Chakraborty and Ewens 2018; G. W. Brown et al. 2019). We focus on the puzzle of investment style drifts - namely the question of why LPs are concerned about style drifts but do not contractually rule them out. To address the question of whether style drifts constitute an agency conflict, this paper starts by laying out that all style drifts carry information about the risk-taking of venture capitalists (VCs). Besides the established view that downwards and upwards stage drifts respectively increase or decrease the risk of a fund, we show that location drifts and industry drifts can also be related to the risk-taking appetite of VCs at the time of investment. Based on this, we differentiate between two groups of hypotheses of potential motivations for investment style drifts, to evaluate whether or not style drifts are in the best interest of LPs. The first group explains style drifts as deliberate risk-taking decisions. We draw on the tournament effect established in the mutual fund literature (K. C. Brown et al. 1996) and apply the concepts of compensation incentives, i.e. increasing one's variable compensation through carried interest, and employment incentives (Kempf et al. 2009), i.e. the fear of losing future income in the form of management fees by not being able to raise a (significant) follow-on fund, in the venture capital context. From a VC's point of view, it is rationale to balance the risk-taking strategy between employment incentives and compensation incentives, however, for the LP this behavior is not desirable. The second group of hypotheses explains drifts as a product of competitive pressure or as a necessity due to cooler than usual exit markets. Drifts out of pressure or necessity would imply that a change in the risk profile of the fund is a side-effect rather than a cause of style drifts, which could be in the best interest of LPs. In contrast, if VCs deliberately alter the fund's risk to benefit from the higher compensation potential of riskier investments and not because it is necessary to do so, style drifts constitute an agency conflict. Only if there is evidence for both groups of hypotheses the puzzle of investment style drifts can be reconciled because LPs must also benefit from leaving GPs freedom in their investment decisions. Lastly, by analyzing fund performance implications of all style drift dimensions the paper adds to the literature about factors influencing private equity performance.

The results of the analysis of 31,521 initial investments in this paper largely support the argument that style drifts represent an agency conflict. They indicate that risk-taking increases when employment incentives are weak and therefore compensation incentives gain in importance. The propensity to style drift into riskier investments is higher when VCs are performing well and when public market conditions are favorable as VCs then feel confident of being able to raise a large follow-on fund. But not all risky style drifts constitute an agency conflict. Industry drifts seem to differ from stage and location drifts, because the analysis of the motivational factors shows, that industry drifts cannot be explained by the same factors. Results indicate that industry drifts might very well be in the best interest of LPs because they are mostly out of necessity. These findings seem to partly unravel the style drift puzzle, as there are 'good' and 'bad' motivations for style drifts from the point of view of a LP. In addition to the investigation into the risk-taking aspect of style drifts, this paper also analyses the subsequent impact of style drifts on individual investment success and overall fund performance. Controlling for the potential endogeneity of style drifts and exit outcomes, the analysis shows that style drifts significantly affect individual investment success in terms of success probability. As LPs allocate their capital into funds and not individual investments, we also analyze the effect of style drifts on overall fund success. Combining all style drifts into a single aggregate style drift measure shows that on average style drifts decrease the exit rate of venture capital funds. For example, a fund without a single style drift in its portfolio, all else equal, has a 7.4 percentage points higher exit rate, than a fund that drifts in at least one style dimension in every single investment.

The remainder of this paper is structured as follows. First, section 2.2 introduces relevant literature about style drifts and risk-taking in venture capital and develops testable hypotheses. Next, section 2.3 showcases the dataset and goes over the main variables of interest, before section 2.4 covers the econometric analysis and discusses the results. Finally, section 2.5 concludes.

2.2 Background and Hypotheses

2.2.1 Style Drifts and Risk-Taking

From a LP's perspective, a venture capital fund is nothing but a vehicle to invest money in. LPs select funds with specific preferred investment styles to realize a desired risk-return allocation for their own portfolio. As with any other investment vehicle, there is a certain risk associated with venture capital in general but also with each specific portfolio a fund builds up over its lifetime in particular. Assessing the risk of a venture capital fund poses a non-trivial challenge compared to other asset classes (Cochrane 2005; Cumming et al. 2005). Because of the lack of an active secondary market for venture capital investments the asset class is highly illiquid. Further, VCs usually do not publish data about their investments. But even when information is available, 'stale pricing', i.e. keeping the valuation of the individual investments at cost until valuations are finally realized or a write-off becomes necessary, constitutes a problem when trying to evaluate risk in venture capital (Gompers and Lerner 1997; Emery 2003). Thus, it is usually impossible to rely on time series of fund returns or volatility for risk estimation.

However, literature has spawned different attempts to measure at least the risk-taking appetite of GPs, as a way to proxy fund risk. For example, Chircop et al. (2020) use syndication and staging behavior as a measure of risk-aversion. Further, other authors show that some specific investment characteristics such as the investment round number (Cochrane 2005) or the portfolio company's development stage (Diller and Kaserer 2009; Buzzacchi et al. 2015), can be related to the specific level of inherent 'investment risk' associated with a deal. Following this line of argument, we propose that the expected investment strategy or style of a fund sets the baseline for a fund's risk profile. Comparing any given investment of a fund with the expected investment style of the same fund then allows for a relative risk assessment in comparison to the initially expected investment style. More precisely, each style dimension of an investment bears some information about the risk-seeking or risk-avoiding behavior of the GP managing the fund. In this sense, it is possible to make a judgment about whether an investment is associated with more than the expected risk based on the preferred investment style. Thus, this relative risk assessment answers the question of whether a GP increases the fund's risk relative to the fund's expected risk profile.

The first style dimension that can be easily connected with the risk-taking attitude of the GP is the development stage of the portfolio company. Startups can be classified according to their development stage into seed stage, early stage, expansion stage, and later stage. A seed-stage startup has yet to prove that it can generate a viable business model, attract employees, and find customers. So, intuitively a seed-stage startup is associated with higher investment risk than a later-stage startup, based on the fact that the probability of failure is inherently much higher than for a later-stage startup, which already revealed much information about its quality. Investing in earlier development stages than expected is therefore clearly associated with a higher risk-taking appetite compared to investing in the expected investment stage.

Second, investing internationally[1] instead of domestically comes with higher risk for the VC, because greater geographical distance and institutional distance (Tykvová and Schertler 2014) between portfolio company and VC lead to weaker monitoring, which is associated with a lower likelihood of a successful exit (Bernstein et al. 2016). This means the increased risk is not per se a characteristic of the portfolio company as is the case with stage drifts. It is rather a sign of the increased risk appetite of the GP because the fund manager is willing to accept higher levels of information asymmetry and a

[1]International investments is defined as investments in companies that are headquartered in a country that is different from the venture capital fund's home country.

decreased ability to monitor an international investment. In line with this argument, Cumming and Dai (2010) find that VCs exhibit weaker local bias when they are more capable of overcoming information asymmetries. For example, a French venture capital fund investing in a Japanese portfolio company can be considered taking on more risk than the same fund investing in a company in France, because the geographical distance and institutional distance make picking a low-quality portfolio company more likely and frequent monitoring more tedious. Nahata et al. (2014) call this the 'liability of foreignness'.

Third, the choice of investment industry also allows making an inference about the relative risk appetite of a VC. VCs benefit from a narrow industry focus and specialization (Norton and Tenenbaum 1993; Sørenson 2008; Gompers et al. 2009), because not all experiential knowledge is valuable across industries. Due to the high information asymmetry in venture capital investments, a high degree of specialization in a few industries is a way for VCs, to decrease the adverse selection risk. As typically core technologies, trends, and markets differ among industries, more specific experience allows VCs to better select the best investment opportunities. This can be related to the seminal work of Akerlof (1970), who introduces the concept of a market for lemons. The paper shows how information asymmetry between buyers and sellers can negatively affect trading in a market. In the matching process of a VC and a potential portfolio company VCs without industry knowledge might only be presented with low-quality investment opportunities that other specialized VCs with focus on the same industry have already declined, i.e. lemons in the sense of the model of Akerlof (1970). While the entrepreneur knows about the true quality of the portfolio company, distinguishing high-quality from low-quality investment opportunities is much harder for unspecialized VCs without industry experience leading to a much higher adverse selection risk and subsequently an increased likelihood of picking a lemon. In addition, staying within the preferred industry also increases the probability of being able to add value to portfolio companies utilizing industry knowledge, which further helps to mitigate part of the inherent idiosyncratic investment risk after the initial selection.

Overall, it is important to note, however, that risk-taking in the context of venture capital investments is not directly equivalent to most other asset classes. Other than in public markets, private information and the possibility to strongly influence the decisions and thus the success probability of portfolio companies via board seats and other value-adding services differentiates VCs' abilities to attenuate negative consequences of deals that are perceived as risky at the time of investment. Chemmanur et al. (2011) show that VCs are not only good at selecting high-quality portfolio companies but that they are also able to add value to portfolio companies after the initial investment. Thus, it is not trivial to predict how the risk-taking attitude of a GP influences individual investment performance and especially fund performance.

2.2.2 Style Drift in the Private Equity Literature

There is only a small niche of literature analyzing style drifts in private equity. More precisely, there are only three noteworthy papers specifically analyzing style drifts in the private equity literature. Cumming et al. (2009) are first in dealing with investment style drifts in private equity. The focus of their paper is on a theoretical model that derives conditions that lead to style drifting for venture capital funds based on signaling theory. They predict that young fund managers (GPs) drift less out of signaling considerations. To attract capital for their future funds, GPs have to prove to LPs that they do not deviate from the expected investment style. They find empirical evidence in support of the theoretical model. However, the paper is limited to investment stage-related style drifts. Other style dimensions are not considered. Further, Cumming et al. (2009) do not link the style drifting activity to the risk-taking attitude of the GP. This means they simply study the extent to which a fund deviates from its stated investment objective in terms of a portfolio company's development stage. This limits the scope of their empirical work, because upward and downward drifts, representing opposite risk-taking decisions, are most likely caused by different factors and because other style drift dimensions are not considered.

Buzzacchi et al. (2015) build on the basic approach of identifying style drifts of Cumming et al. (2009). They use a unique sample of 149 government-supported venture capital funds in Europe to analyze how management incentives influence the propensity of investment stage drifts. Their sample is quite small and might not be representative due to the focus on publicly sponsored European venture capital. The paper's focus is also solely on investment stage drifts and does not consider style drifts concerning industry or location. However, in contrast to the earlier work of Cumming et al. (2009) they separately look at upward and downward stage drifts and consider the risk aspect of the respective drifting directions. They relate the different investment stage drifts to different risk categories and find some limited empirical evidence that funds with a higher number of write-offs tend to upwards drift less, i.e. decrease risk less, than more successful funds. Further, they find that public market conditions positively influence the risk-taking attitude of GPs.

Bubna et al. (2020) look at private equity overall and therefore include classical VC funds as well as buy-out oriented funds in their sample. They deviate strongly in what they define as style drift. Rather than focussing on the ex-ante stated investment goals of a fund, they introduce a vector-based investment style measure that captures variation in investment stage, location, and industry. This measure is designed to capture a relative change of investment style compared to the prior investment year. While they are first in analyzing style drifting in private equity including more than stage drifts, a drawback of their methodology is, that they are not able to investigate style drift on a deal level. The methodology requires Bubna et al. (2020) to calculate the style drift measure on an aggregate VC-firm-year level. Further, their style measure convolutes all three dimensions of style into one single measure. As a result, they cannot analyze the determinants of the individual style dimensions separately and cannot connect style drifting to risk-taking behavior. Their main empirical finding is that the aggregate effect of their style drift score on performance is negative, i.e. style consistency is beneficial to the VC firm performance.

2.2.3 Motivation for and Performance Implications of Style Drifts

Economic theory has spawned several potential explanations for why GPs drift in their style. Not all potential factors driving style drifts automatically constitute an agency conflict between LPs and GPs. First, we focus on potential motivations of style drifts that are based on the assumption that fund managers actively consider investment risk when they decide to drift in their style. This means that the following hypotheses assume style drifts to be deliberate risk-taking decisions, that might not be in the best interest of the LP.

As venture capital funds compete for the capital commitments of limited partners, they implicitly engage in a theoretical fund tournament. K. C. Brown et al. (1996) first introduced the concept of fund tournaments in the context of mutual funds competing for future capital inflows. According to them, mutual fund managers compete in a yearly tournament based on their mid-year performance, in which only highly ranked funds receive significant future capital inflows, by 'winning' the fund tournament. Because compensation is directly related to the fund size in a typical mutual fund fee model[2], there is a strong compensation incentive to reach a high rank in this implicit tournament, to increase assets under management. Thus, according to this compensation incentive, it is rational for poorly performing fund managers in the first half of the tournament to increase their risk in the second half to increase their chance of reaching a top-rank (Chevalier and Ellison 1997). This view assumes that fund managers have much to gain but nothing to lose, by increasing the risk in the second half of the tournament.

[2]Mutual funds usually charge a fixed fee for the assets under management and a variable fee for past performance.

Kempf et al. (2009) introduce a second incentive to consider in these tournaments. Low-performing fund managers in the first half of the tournament might fear losing their jobs if their performance develops even poorer going forward (Khorana 1996; Chevalier and Ellison 1999b). Thus, in this case, the employment incentive, i.e. not losing one's job and future income, should lead to decreased risk-taking compared to other fund managers in the second half of the tournament, to decrease the probability of even worse performance.

While venture capital funds do not follow the same working mechanisms as mutual funds, the general idea with some adaptions is transferable to venture capital funds as well. In contrast to the mutual fund setting, the main compensation incentive for VCs is carried interest, a substantial share of the proceeds of successful investments. The yearly tournament setting with a ranking at each year's end does not directly apply to venture capital funds. Due to the private and closed-end nature of venture capital funds, VCs typically do not accept further inflows into an existing fund during its lifetime after a certain point in time. So, increasing assets under management by attracting further inflows to maximize the fixed management fee should play no role in venture capital. But of course, venture capital firms do also compete for future capital inflows, however, only to establish follow-on funds and subsequently also generate future income. Even though there is no public transparency about current venture capital fund performance, LPs do usually have the possibility to screen the recent investment history of potential VCs on a private basis before they commit capital to a new fund. In a setting where only well-performing venture capital firms can raise a lot of capital for the launch of a new fund (Chung et al. 2012), not being able to attract enough capital at least drastically diminishes a VC's future income potential or at worst even poses a threat for a venture capital firm's continued existence, because their existing funds only have a predetermined finite lifetime. In support of this, Crain (2018) argues that already successful VCs will increase their risk more than poorly performing VCs because their performance going forward will less likely negatively affect their ability to raise a follow-on fund. He also finds empirical evidence that the market for follow-on funds punishes poorly performing VCs more than it rewards well-performing VCs, which is why VCs adapt their investment strategy based on their past performance. Subsequently, this means employment incentives should be much more important for poorly performing VCs in the venture capital industry compared to the mutual fund setting, while compensation incentives based on carried interest are much more pronounced for well-performing VCs.[3] It then follows, that low-performing venture capital firms should be expected to exhibit

[3]The incentive scheme explained here does not rule out the possibility, that some VCs exhibit such a bad performance that they assume that they will not be able to raise a follow-on fund without

a lower risk-taking appetite in comparison to well-performing venture capital firms, to balance the incentive structure between compensation and employment incentives.

H1: Style drifts into riskier investments are more likely for VCs with strong past performance, while style drifts into less risky investments are more likely for VCs with poor past performance

In line with the relationship between past performance and style drifting, Buzzacchi et al. (2015) hypothesize that favorable public market conditions are related to more risk-taking in venture capital. Whereas employment incentives are overall much less pronounced in a booming economy, compensation incentives gain in importance, when stock markets are high. This is underscored by Lahr and Trombley (2020), who find that the likelihood of being able to raise a follow-on fund is higher in boom periods and lower in recession times. Additionally, based on a theoretical model of the market for venture capital, Inderst and Müller (2004) predict that VCs conduct less costly screening of their portfolio companies in hot markets. This directly leads to the conclusion that VCs are willing to accept higher levels of information asymmetry in hot markets, which as explained above, means taking on more investment risk. Bengtsson et al. (2005) find some limited empirical evidence for this prediction. Furthermore, Nanda and Rhodes-Kropf (2013) analyze the role of hot markets in financing more innovative and thus more risky startups and find that VCs invest in riskier startups in hot markets. So overall, riskier style drifts are expected to be more frequent, when public markets are booming.

H2: Style drifts into riskier investments are more likely when public markets are hot

The common motivation of drifting behind the second group of potential style drift determinants is necessity and pressure, rather than the deliberate risk-taking decision assumed so far. Thus, this group of determinants differs from the first one, because the investment risk aspect is not the main factor contributing to the decision to drift, but rather a resulting side effect of the drift decision. Drifts out of necessity might be in the best interest of LPs and could therefore explain why the investment style is not fixated contractually. There are several papers scrutinizing how competition in the venture capital industry influences investment decisions (Gompers and Lerner 2000a; Ljungqvist et al. 2020; Diller and Kaserer 2009). The general setup of venture capital funds as closed-end funds with a limited investment horizon of about 10 years creates some inherent investment pressure. As the general partner is usually obliged to invest a fund's capital within the first years of the fund's lifetime (Cumming and Johan 2013), new capital inflows into venture capital funds lead to an increase of available supply

catching up the performance gap. This would lead these VCs into 'gambling for resurrection by investing in risky investments trying to drastically improve the performance.

of financing for startups seeking funding. This is why VCs looking for high-quality investment opportunities compete against each other in the pursuit of fully investing the fund's capital in time. In their seminal work, Gompers and Lerner (2000a) coin the term 'money chasing deals' by analyzing the impact of capital inflows into the venture capital industry on startup valuations. The basic argument is that fluctuating capital supply needs to be matched with a limited number of high-quality startups, which in turn leads to increased valuations in financing rounds. They find empirical evidence for this argument, which they explain by classical forces of supply and demand. In line with their findings, it is natural to assume that increased capital inflows might subsequently also be related to a higher propensity to style drifts overall. When valuations in the preferred investment style are too high, it might be rationale to drift into alternative styles. While Gompers and Lerner (2000a) focus solely on the supply side of capital, assuming a fixed set of available investment opportunities, the demand side, i.e. the number of high-quality startups seeking financing, fluctuates as well. Ljungqvist et al. (2020) hypothesize that the changes in the level of available deal flow in the preferred investment style, i.e. a potential lack of fitting investment opportunities, might also be related to the increased competition when capital supply is assumed to be fixed in the short run. When fewer promising investment opportunities are available VCs might drift in their style out of necessity, because sticking to the preferred investment style becomes increasingly harder the fiercer the competition among venture capital funds for the few high-quality investment opportunities in the preferred style.

H3a: All style drifts are more likely when fund inflows are high
H3b: All style drifts are more likely when preferred deal flow is low

Another factor explaining style drifts is changes in the current exit market attractiveness. IPOs are widely considered the most attractive exit channel for venture capital investments (Gompers 1996; Cochrane 2005; Cumming et al. 2009). Thus, a high fraction of IPO exits in an industry or country represents an attractive exit market from the venture capitalist's point of view. Hull (2018) argues that it might be necessary for VCs to actively chase returns by leaving their preferred investment industry when the exit market in the preferred investment industry is less attractive than usual. A cool exit market might have detrimental effects on the probability of exiting a portfolio company successfully. The same might be true for country-specific exit markets. This hypothesis is supported by the fact that historically IPOs have been a much less common exit channel for startups in Europe, which is one key reason for the less developed venture capital industry in Europe compared to the United States (Kräussl and Krause 2014; Schwienbacher 2005). Considering that VCs invest with the end, i.e. the exit, in mind, the propensity of style drifts should be higher when the preferred style's exit market attractiveness is lower than usual.

H4: All style drifts are more likely when the preferred exit market attractiveness is low

Besides the motivational factors of style drifts, we are also interested in their consequences for investment success. Performance implications of style drifts are contradictory among existing studies. While Cumming et al. (2009) observe a positive effect of style drift on the performance of venture capital investments, Bubna et al. (2020) come to the opposite conclusion when measuring the firm-level performance implications of their style drift measure. Two reasons for these inconsistent findings might be that the studies measure style drift dissimilarly and performance at different levels. Cumming et al. (2009) measure performance on the investment level, while Bubna et al. (2020) examines the VC firm-level. We argue, that only the fund-level is from practical importance for LPs. LPs typically allocate capital to funds, not to individual investments, or VC firms. This means only performance implications on the fund level are relevant in practice. Further, VC firms usually have multiple funds in parallel. By aggregating style and performance on VC firm-level, the analysis might convolute the individual fund effects.

In this paper, we argue that most style drifts should be detrimental to the probability of exiting an investment successfully. Usually, GPs are eager to employ various mechanisms such as screening, due diligence, and monitoring (Fried and Hisrich 1994; Cumming 2006) to mitigate information asymmetries between investor and portfolio company thereby minimizing the connected adverse selection risk. In a comprehensive survey analyzing VCs' decision-making processes, Gompers et al. (2020) show that VCs even consider deal selection their most important activity to ensure successful investments. However, as argued in section 2.2.1 downwards stage drifts, location drifts, and industry drifts are associated with higher information asymmetry and an increased adverse selection risk compared to style-consistent investments. Consequently, since these riskier style drifts increase the adverse selection risk, they should be associated with worse investment performance.

H5: Style drifts into riskier investments are related to worse investment performance

2.3 Data

2.3.1 Sample and Variable Definitions

Sample Construction

We start building our sample by collecting data about private equity investments from Refinitiv Eikon (formerly known as Thomson Reuters Eikon and Thomson Reuters VentureXpert), a well-established source of data in private equity research (e.g. Gompers et al. 2016; Kaplan and Lerner 2016; Nanda et al. 2020; Y. Li et al. 2014), to which we add stock market data from Thomson Reuters Datastream, country-level cultural dimensions from Hofstede (2001), and a country-level legal system quality index from La Porta et al. (1998) and Berkowitz et al. (2003). We begin with collecting all venture capital investments from 1980 to the end of 2014 conducted by venture capital funds located in the United States of America and Europe[4]. However, we limit the econometric analysis to deals in or after 1985. This timeframe is chosen for three reasons. First, venture capital activity was very limited before 1980. After a change of the Employee Retirement Income Security Act's prudent man rule in the United States in 1979, the industry started to receive high inflows (Gompers 1994). Second, excluding investments before 1985 from the main sample allows us to calculate variables such as past performance over up to 5 years before the investment. And third, by ending the sample in 2014 we make sure that each investment has at least 5 years to be exited.

As we are interested in style drifts in venture capital, we restrict our sample to private equity funds that have been classified as *venture capital* type by the database. Further, we only include funds who identify as *independent private partnership* as investor type, because we are interested in the potential agency conflict between LPs and GPs. This means we exclude all funds with institutional affiliations such as corporate VCs or bank-affiliated VCs. Some funds involved in a deal are not identified (*unspecified fund*) in the database, and some portfolio companies are not assigned to one of ten broad industry groups by the database provider. We exclude all of these observations for our analysis. Further, we restrict the sample to VCs, who have invested in at least 5 companies before the deal at hand to ensure we exclude infrequent investors and outliers in the database and exclude all purely international funds from the sample. Finally, as we are interested in the strategic investment decision of GPs, we follow Cumming et al. (2009) and only include first-time investments in a portfolio company. Follow-on funding

[4]Funds from the following countries in Europe are included in the sample: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, Netherlands, Norway, Portugal, Republic of Ireland, Spain, Sweden, Switzerland, United Kingdom

in later investment rounds bears no further information about the active, strategic investment decision - and thus active style drifts - of a fund.[5] This leaves us with the main sample (*deal-level sample* henceforth) of 31,521 first-time investments into 18,187 unique companies by 1,100 unique venture capital firms operating 3,113 unique funds, for which all relevant independent variables for our analysis of style drift determinants are available. For each observation, our deal-level sample includes information about the venture capital firms and funds involved in a deal, general information about the portfolio company as well as investment round specific information. For the analysis of implications of style drifts on fund performance, we create a second (sub)sample (*fund-level sample* henceforth). Unlike our deal-level sample, this fund-level sample includes all investments, including those for which not all independent variables of the main analysis of style drift determinants are available and in addition to this is limited to all funds which have been founded no later than 2009. This is necessary to make sure that each fund's investment history is fully covered and each fund in the sample has at least 10 years to build and exit its portfolio. This fund-level sample consists of 2,718 VC funds.

Measuring Style Drift and Investment Performance

Key to this paper's analysis is the definition of style drifts. To identify style drifts we rely on the deal-level sample and categorize every observation as either a drift or no drift with a dummy variable equal to one in case of a drift. As we hypothesize that the drivers of style drift differ among style dimensions, we differentiate the three dimensions of style and thus also create a dummy variable for each dimension of style drift.

First, we construct a stage drift variable analogous to Cumming et al. (2009) by comparing a fund's stated stage focus to the stage of the actual investment.[6] Following Buzzacchi et al. (2015), we also take into account the direction of drift by separating upward and downward stage drifts into two variables to capture the opposite risk-taking implication of the respective drift. A downward stage drift occurs when a fund invests in an earlier investment stage than its stated stage focus, e.g. an early-stage fund investing in a seed company. By contrast, an upward stage drift occurs when a fund invests in a later

[5] Not excluding follow-on funding rounds would include passive drifts in the sample. As deciding over further funding rounds is a fundamentally different decision process than a first-time investment, not including these observations makes sure there is no noise added to the data.

[6] The database classifies companies in seed stage, early stage, expansion stage, and later stage. However, the fund's stage focus is only classified in seed stage, early stage, and later stage. For the analysis, we treat expansion-stage and later-stage companies both as later stage, when comparing fund focus and investment stage, i.e. a later stage fund investing in an expansion stage portfolio company does not resemble a style drift.

investment stage than originally stated as stage focus, e.g. an early-stage fund investing in a later stage company. For funds without a stage focus (balanced stage funds) stage drift is consequently not defined, and seed-stage funds can only drift upwards, while later-stage funds can only drift downwards.

Next, we focus on location drifts. As explained in section 2.2.1 the expected investment behavior of a typical fund is to invest in companies headquartered in the same country as it is located itself. We thus follow earlier research focussing on VC internationalization (Schertler and Tykvová 2011; Tykvová and Schertler 2014; Cumming et al. 2016b) in treating every cross border investment as a location drift, i.e. a location drift occurs when e.g. a US fund invests in a non-US portfolio company.[7] Finally, we measure industry drifts by identifying a fund's preferred investment industries and deviations from these preferences. We use the database's industry classification scheme into ten broad industry groups[8] to determine the fund's preferred industries. The two industries in which a fund has made the largest number of first-time investments before the investment at hand are assumed to be the preferred investment industries. This means in theory the preferred industries can change over time, which is in line with the specialization effect described in section 2.2.1. Given the broad industry classification into only ten industry groups, investing outside these preferred industries can be interpreted as a considerable industry style drift.[9] Consequently, an industry drift occurs, when a fund invests into a portfolio company outside its two preferred industries.

Measuring investment performance is a common issue researchers face when dealing with venture capital investments. The lack of detailed cash flow data in the sample makes it impossible for us to compute investment returns. Thus, we rely on exit success as widely used proxy for performance (e.g. Bottazzi et al. 2008; Nahata 2008; Y. Li et al.

[7]We also consider another location drift definition in section 2.4.1, that takes the factor of geographical distance more into account. In this alternative definition, we classify only out-of-region investments as a location drift. For the sample, this specifically means, that investments from a European fund within Europe are not classified as a location drift. This alternative definition should thus emphasize the risk component of a location drift more than the main definition in this paper.

[8]See table 2.3 panel C for an overview of all industries.

[9]In the sample, the top two investment industries make up the majority of all fund investments for over 97% of all funds. This emphasizes that funds are typically industry-focused and our definition of the preferred investment industries is accurate. Nevertheless, as we have to identify industry focus from the investment pattern of a fund, we also consider alternative definitions of industry drifts in the regression analysis in section 2.4.1 that are defined even narrower around the increased risk-taking attitude as a robustness check. The first alternative definition only treats investments into industries in which the fund has had no more than one prior investment as a drift and the second alternative definition categorizes all investments in which the VC firm has not had more than one investment in the last six years as an industry drift. Defining industry drifts based on these rare investment events, should make sure that the investments are not in the fund's preferred investment style and represent investments outside the area of specialization.

2014; Bengtsson and David H. Hsu 2015). VCs make their profit almost exclusively via successful exits through an IPO or trade sale. Therefore, we create a dummy variable (*Success*) for investment success which takes the value of one when a portfolio company ultimately got acquired or went public. While cashflow data would allow for more precise measurement of performance, Gompers and Lerner (2000b) show that investment success is a robust proxy. For the fund-level performance, this means that the *Exit Rate*, i.e. the fraction of successful exits, is a good proxy (Hochberg et al. 2007).

Explanatory Variables

To test the hypotheses from section 2.2.3 this paper includes a set of explanatory variables linked to the hypotheses and some control variables to account for investor and deal characteristics. Tables 2.1 and 2.2 give an overview of all variables used in the econometric analysis in section 2.4 both for the deal-level analysis and the fund-level analysis. Furthermore, the key variables are explained in detail in the main text.

Past Performance: In an ideal case, it would be possible to measure aggregate VC firm performance based on actual cash flows. However, as discussed above, this information is not available for this paper. Prior studies (Kaplan and Schoar 2005; Hochberg et al. 2007) use the performance of the last fund to proxy for past performance, but this would considerably limit the deal-level sample to follow-on funds that have no time overlap with their predecessor. Thus, to test **H1**, past performance on the firm level is measured indirectly as follows: First, we construct a theoretical exit date for every unsuccessful investment. As our sample does not provide any information about when an actual write-off or a liquidation occurs, we use the investment stage-dependent average time-to-exit of the successful investments in our sample and add that to the known investment date to estimate the time by when an unsuccessful investment should have been exited successfully.

Table 2.1.: Overview and Definition of Main Variables of Interest for Deal-Level Analysis

This table provides and overview and the definition of all variables used in the deal-level regression analyses of the sample of 31,521 first time investments. The sample covers investments conducted between 1984 and 2014. Funds from the United States of America and the following countries in Europe are included in the sample: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, Netherlands, Norway, Portugal, Republic of Ireland, Spain, Sweden, Switzerland, United Kingdom

Variable Name	Definition
Dependent Variables	
Stage Drift Down	A dummy variable indicating a downward stage drift for the venture capital fund with one, and zero otherwise. A downward stage drift occurs when a fund invests in an earlier investment stage than its stated stage focus.
Stage Drift Up	A dummy variable indicating an upward stage drift for the venture capital fund with one, and zero otherwise. An upward stage drift occurs when a fund invests in a later investment stage than originally stated as stage focus.
Location Drift	A dummy variable indicating a location drift for the venture capital fund with one and zero otherwise. A location drift occurs when a fund invests outside its headquarter country.
Industry Drift	A dummy variable indicating an industry drift for the venture capital fund with one and zero otherwise. An industry drift occurs when a fund invests in a portfolio company outside its two preferred industries.
Success	A dummy variable equal to one when a portfolio company ultimately got acquired or went public, and zero otherwise.
Explanatory Variables	
Past Performance	The fraction of successful exits of all potential exits of the venture capital firm in the 5 years preceding the investment in question minus the average fraction of successful exits of all potential exits of all VC investments in the 5 years preceding the investment.
MSCI World	The change of the MSCI World Index between the investment and the fund's founding date.
Fund Inflows	The inflation corrected sum of region-specific inflow of capital into new funds in the two years preceding the investment.
Deal Flow	The number of deals in the fund's preferred style in the year preceding the investment divided by the number of VCs active in the respective style in the same time interval.
Exit Market Attract.	The fraction of IPOs of all successful exits in the fund's preferred style in the year preceding the investment minus the three-year moving average.
Drift Score (excl. Stage Up)	The number of style drifts per portfolio company, not counting (less risky) upwards stage drifts.
1 Drift, 2 Drifts, 3 Drifts	A set of dummy variables equal to one when *Drift Score (excl. Stage Up)* is equal to the respective number of drifts, and zero otherwise.
Controls	
Round Number	The numeric sequence of the investment round.
No. of Investors	The number of funds participating in the investment round.
Experience	The natural logarithm of the number of prior investments by the venture capital firm.
First Fund	A dummy variable equal to one when a fund is the first fund of the venture capital firm and zero otherwise.
Fund Size	The natural logarithm of the fund's size in 1985-Dollar.
Fund Age	The age of the venture capital fund at the time of investment.
Invested Amount	The dollar amount invested in the portfolio company at the time of investment.
Syndication	A dummy equal to one when a deal is syndicated and zero otherwise.
MSCI World (Exit Year)	The return of the MSCI World in the exit year.
Uncertainty Avoidance	The Hofstede uncertainty avoidance index (Hofstede 2001) for the fund's country.
Legal System Quality	An index measuring the legal system quality of the portfolio company's country based on data from La Porta et al. (1998) and methodology from Berkowitz et al. (2003).

We then calculate the fraction of successful exits of all potential exits of the venture capital firm in the 5 years preceding the investment in question.[10] Finally, we calculate the excess past performance by subtracting the average fraction of successful exits of all potential exits of all VC investments in the 5 years preceding the investment in question from the VC firm's individual performance. This measure is designed in a way that VC firms underperforming their peers have a negative sign for past performance, while VC firms over-performing their peers have a positive sign for past performance. This

Table 2.2.: Overview and Definition of Main Variables of Interest for Fund-Level Analysis

This table provides and overview and the definition of all variables used in the fund-level regression analyses of the sample of 2,718 funds. The sample covers funds with vintage years between 1985 and 2009. Funds from the United States of America and the following countries in Europe are included in the sample: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, Netherlands, Norway, Portugal, Republic of Ireland, Spain, Sweden, Switzerland, United Kingdom.

Variable Name	Definition
Dependent Variables	
Exit Rate	The fraction of a fund's portfolio companies that have been successfully exited via an IPO or trade sale.
Explanatory Variables	
Stage Drift Down	The fraction of a fund's portfolio companies that represent a downwards stage drift. A downward stage drift occurs when a fund invests in an earlier investment stage than its stated stage focus.
Stage Drift Up	The fraction of a fund's portfolio companies that represent an upwards stage drift. An upward stage drift occurs when a fund invests in a later stage than originally stated as stage focus.
Location Drift	The fraction of a fund's portfolio companies that represent a location drift. A location drift occurs when a fund invests outside its headquarter country.
Industry Drift	The fraction of a fund's portfolio companies that represent an industry drift. An industry drift occurs when a fund invests in a portfolio company outside its two preferred industries.
Drift Share	The fraction of all investments that represent at least a drift in one style dimension.
Drift Share (excl. Stage Up)	The fraction of all investments that represent at least a drift in one style dimension, not counting (less risky) upwards stage drifts.
Average Drift Score	The average number of style drifts per portfolio company.
Average Drift Score (excl. Stage Up)	The average number of style drifts per portfolio company, not counting (less risky) upwards stage drifts.
Controls	
Fund Sequence	The natural logarithm of the position of the fund in the chronological order of all funds of the venture capital firm.
Fund Sequence squared	The natural logarithm of the squared position of the fund in the chronological order of all funds of the venture capital firm.
Fund Size	The natural logarithm of the fund size in dollars.
Fund Size squared	The natural logarithm of the squared fund size in dollars.

captures the effect of the relative performance assessment of VC firms, which is similar to the ranking model of fund tournaments described in section 2.2.3.

[10]We use 5 years, as this makes the measure less sensitive to the way we calculate the theoretical exit date. Using 2 years also delivers very similar results.

MSCI World: To test **H2** we use the development of the MSCI World index as an indicator for public market conditions. The variable measures how public market conditions have changed since the fund was originally raised. We compute the percentage change of the MSCI World index between the time of the investment at hand and the founding date of the fund. This way this variable captures how the public market conditions have changed since the investment focus of the fund was originally set.
Fund Inflows: Following Gompers and Lerner (2000a) and Hochberg et al. (2007), we use the money raised by VC funds according to their vintage year to proxy for competition on the supply side of capital to test **H3a**. This variable is constructed using inflation-adjusted 1985-Dollars, to account for the time value of money over the long period of our deal-level sample. For every investment, we compute the fund inflows over the two years preceding the investment. As competition is strongest among funds operating in the same region, we calculate this variable region-specific based on the fund's home region. We differentiate between Europe and the US regarding fund inflows for our main analysis. In the regressions, the variable is transformed and used in its natural logarithmic form.
Deal Flow: The number of entrepreneurial projects a VC has access to and evaluates is not observable without first-hand access to the private information of a VC firm. Therefore, we create a proxy for the available deal flow in the VC's preferred investment style to test **H3b**. We differentiate between deal flow in the preferred stage, location, and industries. We compute the proxy by taking the number of deals in the preferred style in the year preceding the investment divided by the number of VCs active in the respective style in the same time interval.[11] This measure indicates how many deals have been available per VC in the respective investment style.
Exit Market Attractiveness: We use the fraction of IPOs, i.e. the number of IPOs divided by all exits, to proxy for exit market attractiveness. As we are interested in the question of whether or not lower than usual exit market attractiveness in an industry or country is related to a higher propensity to drift (**H4**), we compute this variable as the difference between the IPO fraction in the year preceding the investment and the average IPO fraction between four and one years before the investment in the respective country or industry. This measure is designed, so that lower than usual exit market attractiveness has a negative sign, while a higher than usual exit market attractiveness has a positive sign. We construct the proxy this way to account for the differences between countries and industries regarding the absolute level of IPO frequency. The rationale is that VCs

[11] For Example: For an early-stage fund based in the United States, whose preferred industries are 'Communications and Media' & 'Computer Software and Services' we compute the deal flow for early-stage deals, the deal flow of US deals, and the deal flow of deals in the 'Communications and Media' & 'Computer Software and Services' industries, to proxy for competition for available deal flow among funds in the preferred stage, location, and industries, respectively.

preferring industries or countries with low or high levels of IPOs as exit channel are only sensitive to a relative change of the exit market attractiveness because they take the absolute level as given for an industry or country.

Controls: We include deal and investor characteristics as controls. This includes the *Round Number*, i.e. the numeric sequence of the investment round, *No. of Investors*, i.e. the number of funds participating in the investment round, *Experience*, i.e. the natural logarithm of the number of prior investments by the venture capital firm, *First Fund*, a dummy variable indicating whether a fund is the first fund of the venture capital firm, *Fund Size* as the natural logarithm of the fund's size in 1985-Dollar, and the *Fund Age*, i.e. the age of the venture capital fund at the time of investment.

2.3.2 Sample Description

Table 2.3 describes the characteristics of the deal-level sample with a focus on the style drift characteristics. Overall the average portfolio company receives 9.8 million US Dollars of funding per investment round and the median investment year is 2000. In the full sample, 15% of all deals represent a downward stage drift for the fund investing in the portfolio company, whereas 23% of all investments constitute an upward stage drift. Industry drifts (50%) are the most common drift type, even when treating upward and downward stage drift as one drift dimension, and both, stage and industry drifts, are more common than location drifts (10%). The drift score is the sum of all drift types, i.e. it represents the average number of drifts of any kind per investment. A drift score of 0.98 means that on average almost every investment represents some kind of drift. Panel A, however, shows that the number of drifts per investment differs in the sample. There are 8,696 investments with no drift at all and only 594 investments with a drift in every style dimension in parallel. For the full sample, about 55% of all investments are exited successfully. However, as expected due to the risk increase, the success rate declines with an increase of the drift score in Panel A, even though there is a large share of (less risky) upwards stage drift in the highest drift score category.

In Panel B the sample is split into three major world regions, based on where the portfolio company is headquartered. It is noteworthy that the overwhelming majority (84%) of all investments in the sample are into portfolio companies in the United States. Still, with 5,064 investments outside the US, our sample is large enough for further analysis. Furthermore, the median investment year indicates, that investments in Europe and Rest of World are more recent compared to the US investments. Entrepreneurial ventures in Europe are also funded with considerably less money (6.4 million USD) compared to the US (10.2 million USD) and RoW (11.2 million USD). Overall, 59% of all investments in

US portfolio companies are successfully exited, whereas in Europe the success rate is only 34%. As can be expected due to the proximity of European countries, the share of location drifts in European investments is much larger compared to the US investments (33% vs. 2%).

Panel C splits the sample into the development stage of the portfolio company at investment time. In line with expectations the later the stage the higher is the investment amount per round. It is interesting to see, that location drifts are more common in later stages. This might indicate that VCs are willing to accept the higher level of information asymmetry related to cross-border investments in exchange for the lower information asymmetry typically connected with later-stage portfolio companies that already revealed much information about their quality. This is a supporting indication for the fact that investing abroad is riskier for VCs and that they might be actively trying to mitigate this risk already at the time of investment.

Panel D sorts the investments according to the industry group of the portfolio company. The median investment year indicates that Biotechnology (2003) has seen much more recent investment activity, compared to Computer Hardware (1995) or Consumer Related (1996). Typical investment amounts (between 5.8 and 12.4 million US dollars) and success rates (ranging from 36%-64%) and industry drifts (34%-79%) differ strongly among industries.

The most noteworthy insight from Panel E is the observation that industry drift scores decrease with increasing investment size. VCs appear to stay more style consistent regarding the investment industry the more they invest. Finally, Panel F shows how the sample distributes over time. The years around the Dotcom bubble (1997-2002) make up a substantial (32%) share of the sample. As expected the average investment size is the highest during this time. Somehow counterintuitively, the overall drift score is the second-lowest (0.96) compared to the other periods. This means that VCs stuck to their style more than in all other periods besides the 2009-2014 period (0.86). It is also interesting to note that the average success rate decreases over time. While 66% of all investments between 1985-1990 were exited successfully, only 34% of the investments between 2009-2014 were exited successfully as well. Industry drifts have steadily decreased over time from 65% (1985-1990) to 37% (2009-2014). This means that VC funds have become more specialized regarding their preferred investment industry over time or have become more style consistent in their investment decisions regarding the portfolio company's industry.

Table 2.3.: Sample Composition and Descriptive Statistics at Deal-Level

This table provides aggregate style drift and investment information about the deal-level sample of 31,521 first-time investments. Each observation represents an investment by a venture capital fund into a portfolio company. The sample covers investments conducted between 1984 and 2014. Funds from the United States of America and the following countries in Europe are included in the sample: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, Netherlands, Norway, Portugal, Republic of Ireland, Spain, Sweden, Switzerland, United Kingdom. The table shows median values for the investment year. Means are shown for all other values. Invested amount is the amount invested by all funds at the respective investment date. Downward stage drift, upward stage drift, location drift, and industry drift are style drifts in the respective dimensions. Score is the sum of all individual drifts. Exit success is a dummy equal to one when a portfolio company ultimately got acquired or went public. Panel A divides deals according to their drift score. Panel B separates the sample according to the home country of the portfolio company. Panel C separates the sample along the development stage of the portfolio company. Panel D categorizes the sample according to the portfolio company's industry group. Panel E differentiates among investment amount quartiles. In Panel F the transactions are differentiated according to the investment period in which they took place.

	Observations	Year	Invested Amount*	Drift					Exit Success
				Stage Down	Stage Up	Location	Industry	Score	
Full Sample	31,521 (100%)	2000	9.8	0.15	0.23	0.10	0.50	0.98	0.55
Panel A: Investment Drift Score									
0 Drifts	8,696 (28%)	2001	10.5	0.00	0.00	0.00	0.00	0.00	0.56
1 Drift	15,404 (49%)	2000	9.5	0.14	0.21	0.06	0.59	1.00	0.56
2 Drifts	6,827 (22%)	2001	9.1	0.34	0.52	0.23	0.91	2.00	0.53
3 Drifts	594 (2%)	2003	13.0	0.26	0.74	1.00	1.00	3.00	0.42
Panel B: Company Region									
Europe	3,930 (12%)	2004	6.4	0.12	0.32	0.33	0.54	1.31	0.34
Rest of World	1,134 (4%)	2004	11.2	0.08	0.26	1.00	0.53	1.86	0.38
USA	26,457 (84%)	2000	10.2	0.15	0.22	0.02	0.50	0.89	0.59
Panel C: Company Stage									
Seed Stage	6,297 (20%)	1998	4.6	0.62	0.00	0.06	0.53	1.22	0.54
Early Stage	11,344 (36%)	2001	8.2	0.06	0.05	0.09	0.48	0.68	0.51
Expansion Stage	10,050 (32%)	2000	12.3	0.00	0.50	0.13	0.51	1.14	0.58
Later Stage	3,830 (12%)	2003	16.3	0.00	0.44	0.10	0.51	1.05	0.64
Panel D: Company Industry Group									
Biotechnology	3,038 (10%)	2003	11.4	0.21	0.19	0.13	0.50	1.04	0.64
Comm. & Media	3,244 (10%)	2000	12.4	0.14	0.22	0.09	0.73	1.19	0.61
Computer Hardware	1,600 (5%)	1995	8.4	0.13	0.23	0.06	0.77	1.18	0.56
Software & Services	7,378 (23%)	2001	8.1	0.12	0.27	0.08	0.35	0.83	0.60
Consumer Related	1,125 (4%)	1996	5.8	0.13	0.18	0.11	0.73	1.15	0.38
Industrial/Energy	1,164 (4%)	2001	6.4	0.13	0.20	0.10	0.79	1.22	0.38
Internet Specific	5,957 (19%)	2000	11.5	0.12	0.24	0.10	0.34	0.80	0.49
Medical/Health	4,091 (13%)	2001	9.4	0.20	0.21	0.09	0.41	0.91	0.59
Other Products	1,438 (5%)	2000	8.9	0.13	0.19	0.15	0.77	1.23	0.36
Semicon./Other Elect.	2,486 (8%)	2001	10.3	0.14	0.24	0.11	0.66	1.15	0.57
Panel E: Investment Size									
1st Quartile	7,882 (25%)	1999	3.4	0.19	0.20	0.10	0.55	1.05	0.48
2nd Quartile	7,879 (25%)	1999	5.4	0.18	0.19	0.07	0.53	0.98	0.57
3rd Quartile	7,881 (25%)	2001	9.4	0.13	0.25	0.10	0.49	0.96	0.57
4th Quartile	7,879 (25%)	2002	20.9	0.08	0.28	0.12	0.45	0.93	0.59
Panel F: Investment Time Period									
1985-1990	4,560 (14%)	1988	4.0	0.18	0.14	0.05	0.65	1.03	0.66
1991-1996	3,961 (13%)	1994	4.8	0.22	0.16	0.06	0.58	1.02	0.68
1997-2002	10,122 (32%)	2000	14.0	0.13	0.24	0.11	0.48	0.96	0.58
2003-2008	8,657 (27%)	2005	10.2	0.12	0.29	0.12	0.48	1.01	0.51
2009-2014	4,221 (13%)	2011	9.5	0.13	0.25	0.11	0.37	0.86	0.34

* in million USD

In table 2.4 the fund-level sample composition is illustrated. There are 2,718 funds with an average of 14 portfolio companies in the sample and the average fund size is 149 million USD. In this table, all values are on the fund level. The drift statistics and success statistics are the fraction of investments that match the respective category. Thus, for the full sample, the statistics are roughly equal to what table 2.3 has shown for the full deal-level sample. This is no surprise, due to how the data was aggregated to reach a fund level. Again, Panel A indicates that higher drift scores on the fund level are associated with lower fund performance measured as the fraction of successfully exited portfolio companies.

Panel B separates the sample into fund headquarter regions. Roughly one quarter of all funds in the sample are European. These funds are on average about half the size of US funds. The stage drift scores indicate that US funds are stage drifting less upwards (24% vs. 34%) and additionally more downwards (15% vs. 13 %), while location drift are much more common in Europe (5% vs. 26%).

Panel C shows that 55% of all funds have an early-stage focus. This number is much larger than the fraction of early-stage portfolio companies (36%) in Panel C of table 2.3. In combination with the large fraction of stage drifts (60%), this can be seen as indicative for **H3b** which predicts more drifts when deal flow in the preferred style is low and thus competition is high. In Panel D funds are split into fund size quartiles. The average fund size in the sample ranges from 11 million USD in the lowest quartile up to 440 million USD in the highest quartile. Intuitively, larger size funds have more portfolio companies. It is noteworthy that larger funds appear to drift less across all dimensions but location and at the same time have a higher performance than smaller funds.

Panel E splits the sample into vintage year time periods. Fund sizes have become larger over time, but at the same time, counterintuitively, the average portfolio size has decreased comparing older funds with more recent funds. Over time funds have become more style consistent albeit this development is almost completely driven by fewer industry drifts. The average fraction of industry drifts has declined from 56% (1985-1989) to 39% (2005-2009) over time, while the fraction of location drifts has steadily increased from 5% to 11%. Table 2.5 displays the mean values for all explanatory variables of the full sample used in the main analysis. In addition to the full sample, the table includes the results of t-tests that we run to compare the independent variables regarding differences among drift and no-drift groups for every style dimension separately. Given the large sample size, most differences are statistically significant at the 1% level. The simple univariate setting of the analysis does give a first impression of the data, but the univariate results should be noted with care.

Table 2.4.: Sample Composition and Descriptive Statistics at Fund Level

This table provides fund information and aggregate style drift characteristics about the fund-level sample of 2,718 funds. Each observation represents a venture capital fund. The table shows mean values for all variables. The sample covers funds with vintage years between 1985 and 2009. Funds from the United States of America and the following countries in Europe are included in the sample: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, Netherlands, Norway, Portugal, Republic of Ireland, Spain, Sweden, Switzerland, United Kingdom. Fund size is the capital committed to the fund. Portfolio size is the number of portfolio companies the fund invested in. Downward stage drift, upward stage drift, location drift and industry drift are the fraction of style drifts in the respective dimensions in relation to all of the fund's investments. Score is the sum of all individual drift fractions. Exit rate is the fraction of the fund's successfully exited portfolio companies. Panel A divides funds according to their average drift score. Panel B separates the sample according to the fund's home region. Panel C separates the sample based on the fund's stage focus. Panel D differentiates among fund size quartiles. In Panel E the sample is split into time periods based on the fund's vintage year.

	Observations	Fund Size*	Portfolio Size	Drift					Exit Rate
				Stage Down	Stage Up	Location	Industry	Score	
Full Sample	2,718 (100%)	149	14	0.14	0.26	0.10	0.45	0.96	0.50
Panel A: Fund Average Drift Score									
Drift Score ≤ 0.5	432 (16%)	179	12	0.03	0.02	0.02	0.27	0.34	0.52
0.5 < Drift Score ≤ 1.0	1,146 (42%)	156	14	0.13	0.18	0.06	0.43	0.80	0.52
1 < Drift Score ≤ 1.5	902 (33%)	133	15	0.20	0.41	0.11	0.53	1.26	0.49
1.5 < Drift Score	238 (9%)	125	13	0.19	0.55	0.39	0.61	1.76	0.43
Panel B: Fund Region									
Europe	624 (23%)	83	11	0.13	0.34	0.26	0.49	1.22	0.33
USA	2,094 (77%)	169	15	0.15	0.24	0.05	0.44	0.89	0.55
Panel C: Fund Stage Focus									
Balanced Stage	719 (26%)	194	15	0.00	0.00	0.10	0.46	0.57	0.51
Seed Stage	186 (7%)	48	12	0.00	0.65	0.06	0.48	1.20	0.42
Early Stage	1,483 (55%)	134	14	0.20	0.40	0.10	0.44	1.15	0.49
Later Stage	330 (12%)	177	13	0.28	0.00	0.11	0.47	0.86	0.57
Panel D: Fund Size									
1st Quartile	681 (25%)	11	9	0.15	0.31	0.07	0.49	1.01	0.43
2nd Quartile	678 (25%)	41	12	0.15	0.27	0.10	0.48	1.01	0.48
3rd Quartile	680 (25%)	106	14	0.14	0.26	0.11	0.44	0.96	0.53
4th Quartile	679 (25%)	440	20	0.13	0.21	0.13	0.40	0.88	0.56
Panel E: Fund Vintage Year									
1985-1989	320 (12%)	51	16	0.18	0.20	0.05	0.56	0.99	0.61
1990-1994	158 (6%)	78	17	0.23	0.19	0.08	0.52	1.02	0.62
1995-1999	788 (29%)	131	15	0.15	0.27	0.10	0.45	0.97	0.54
2000-2004	867 (32%)	181	14	0.11	0.30	0.11	0.45	0.98	0.49
2005-2009	585 (22%)	201	12	0.14	0.26	0.11	0.39	0.90	0.37

* in million USD

In support of **H1** that predicts riskier style drifts to be more likely for well-performing VCs, *Past Performance* is significantly higher for the downward stage drifts compared to the respective no-drift group. *Past Performance* is lower for the upward stage drift group, however, the difference is not statistically significant. The location drift group also shows the expected difference, however, it is not significant. In contrast to what we hypothesize, in the case of industry drifts, the very opposite is true. *Past Performance* is significantly lower for the industry drift group. This is the first indication, that industry drifts might not be driven by the same underlying risk-taking rationale as stage and location drifts. We will further discuss this finding in section 2.4. The group-mean comparisons of the *MSCI World* variable also lend support to **H2** for all drift dimensions, but location drifts. Riskier drifts exhibit higher MSCI World values than the respective no-drift groups for stage and industry drifts. For example, the average *MSCI World* change is 25% for the group that did not downward stage drift vs. 41% for the group that did downward stage drift. In this univariate comparison, there is little support for **H3a**. In fact, only the comparison for upwards stage drifts shows the expected difference of higher *Fund Inflows* for the group that represents upward stage drifts. However, the univariate setting is too simplistic for this analysis. In an unreported analysis, the sample is split into just the European and just the US funds. Within these subsamples, regional *Fund Inflows* show the expected pattern regarding location drifts. *Fund Inflows* in the within region comparison are in fact higher for the location drift group. This will be further analyzed in the multivariate analysis in section 2.4. *Deal Flow* shows the expected pattern for all style drift dimensions but downward stage drifts. In line with **H3b**, the drift groups have consistently significantly lower deal flow compared to the no-drift comparison groups in the corresponding *Deal Flow* variable. There is also some evidence for **H4** concerning the chasing returns hypothesis. In the case of industry drifts, the drifting group exhibits a significantly lower *Exit Market Attractiveness*, which supports the notion that VCs tend to invest outside their preferred industry more when the exit market is not as hot as usual. In the case of location drifts, however, the opposite is the case.

Table 2.6 provides the pairwise correlation coefficients for all variables used in the main analysis. Because of the large sample size, almost all coefficients are significant at the 1% level. The coefficients are in line with the comparison analysis above and give insight into potential multicollinearity issues in the regression analysis.

Table 2.5.: Descriptive Statistics and Mean Comparison of Style Drift Determinants

This table reports mean values of explanatory variables for the full deal-level sample. Further, the sample is split according to the style drift dimensions. The sample covers investments conducted between 1984 and 2014. Funds from the United States of America and the following countries in Europe are included in the sample: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, Netherlands, Norway, Portugal, Republic of Ireland, Spain, Sweden, Switzerland, United Kingdom. The sample consists of all first time investments made by venture capital funds in portfolio companies. Funds without stage focus or seed focus are excluded from the sample when analyzing downward stage drifts, as downward stage drift is not defined for those cases. Funds without stage focus or later stage focus are excluded from the sample when analyzing upward stage drifts, as upward stage drift is not defined for those cases. *Past Performance* is the share of successful exits of all investments of the venture capital firm minus the average performance in the 5 years preceding the investment. *MSCI World* is the change of the MSCI World Index between the investment and the fund's founding date. *Fund Inflows* is the inflation corrected sum of region specific inflow of capital into new funds in the two years preceding the investment. *Deal Flow* is the number of deals in the preferred style in the year preceding the investment divided by the number of VCs active in the respective style in the same time interval. *Exit Market Attract.* is the fraction of IPOs of all successful exits in the fund's preferred style in the year preceding the investment minus the three year moving average. *Round Number* is the numeric sequence of the investment round. *No. of Investors* is the number of funds participating in the investment round. *Experience* is the natural logarithm of the number of prior investments by the venture capital firm. *First Fund* is a dummy variable indicating whether a fund is the first fund of the venture capital firm. *Fund Size* is the natural logarithm of the fund's size in 1985-Dollar. *Fund Age* is the age of the venture capital fund at the time of investment. For each drift type the table shows t-statistics to compare the subsamples of drift and no-drift for the respective style dimension. *, **, *** refer to significance at 10%, 5%, and 1%, respectively.

Variable	Full Sample (N=31,521)	Stage Drift Down			Stage Drift Up			Location Drift			Industry Drift		
		No (15,354)	Yes (4,575)	t-test t-value	No (10,797)	Yes (7,286)	t-test t-value	No (28,422)	Yes (3,099)	t-test t-value	No (15,641)	Yes (15,880)	t-test t-value
Explanatory Variables													
Past Performance	0.07	0.08	0.10	-4.25***	0.08	0.08	1.23	0.07	0.08	-0.54	0.10	0.05	19.14***
MSCI World	0.38	0.29	0.44	-11.2***	0.28	0.29	-0.65	0.43	0.41	0.74	0.34	0.51	-15.87***
Fund Inflows[1]	12.44	14.06	10.72	14.22***	12.36	13.17	-3.93***	12.61	11.39	4.66***	13.25	11.75	9.67***
Deal Flow (Stage)	1.80	2.73	2.88	-5.62***	2.13	2.04	9.98***	1.82	1.81	0.18	1.85	1.78	3.49***
Deal Flow (Country)	7.50	7.18	7.70	-11.8***	7.29	6.96	8.31***	7.72	5.39	48.87***	7.39	7.59	-6.79***
Deal Flow (Industry)	3.67	3.70	3.63	2.98***	3.65	3.65	0.08	3.66	3.63	1.31	3.90	3.42	27.97***
Exit Market Attract. (Country)	-0.04	-0.03	-0.04	4.76***	-0.03	-0.03	-0.63	-0.04	-0.03	-4.76***	-0.03	-0.05	8.63***
Exit Market Attract. (Industry)	-0.05	-0.04	-0.05	2.55**	-0.04	-0.05	1.83*	-0.05	-0.04	-3.97***	-0.04	-0.06	13.97***
Control Variables													
Round Number	2.03	2.23	1.29	34.46***	1.35	2.71	-62.86***	2.03	2.02	0.33	2.05	2.01	2.09**
No. of Investors	4.27	4.32	3.59	14.39***	3.54	4.73	-28.25***	4.34	3.70	10.44***	4.25	4.29	-1.18
Experience	219.59	240.51	264.47	-3.74***	274.33	228.13	7.74***	235.55	198.73	5.74***	228.98	234.83	-1.53
First Fund	0.14	0.13	0.14	-1.57	0.11	0.14	-5.42***	0.14	0.15	-1.59	0.15	0.14	3.48***
Fund Size[2]	113.17	120.53	99.95	7.96***	107.81	106.56	0.56	118.30	165.47	-12.15***	126.68	119.25	3.21***
Fund Age	3.20	2.99	3.01	-0.39	2.75	3.15	-9.48***	3.31	3.47	-2.17**	3.10	3.56	-10.88***

[1] in billion 1985-USD, [2] in million 1985-USD

Table 2.6.: Correlation Matrix of Variables in the Style Drift Determinants Analysis

This table presents a pairwise correlation matrix of the independent variables used in the deal-level main analysis. The sample covers 31,521 first time investments conducted between 1984 and 2014. Funds from the United States of America and the following countries in Europe are included in the sample: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, Netherlands, Norway, Portugal, Republic of Ireland, Spain, Sweden, Switzerland, United Kingdom. *Past Performance* is the share of successful exits of all investments of the venture capital firm minus the average performance in the 5 years preceding the investment. *MSCI World* is the change of the MSCI World Index between the investment and the fund's founding date. *Fund Inflows* is the inflation corrected sum of region specific inflow of capital into new funds in the two years preceding the investment. *Deal Flow* is the number of deals in the preferred style in the year preceding the investment divided by the number of VCs active in the respective style in the same time interval. *Exit Market Attract.* is the fraction of IPOs of all successful exits in the fund's preferred style in the year preceding the investment minus the three year moving average. *Round Number* is the numeric sequence of the investment round. *No. of Investors* is the number of funds participating in the investment round. *Experience* is the natural logarithm of the number of prior investments by the venture capital firm. *First Fund* is a dummy variable indicating whether a fund is the first fund of the venture capital firm. *Fund Size* is the natural logarithm of the fund's size in 1985-Dollar. *Fund Age* is the age of the venture capital fund at the time of investment. *, **, *** refer to significance at 10%, 5%, and 1%, respectively.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Past Performance	(1)	1.00													
MSCI World	(2)	-0.08***	1.00												
Fund Inflows	(3)	0.04***	-0.1***	1.00											
Deal Flow (Stage)	(4)	0.05***	-0.02***	0.18***	1.00										
Deal Flow (Country)	(5)	-0.01	0.18***	0.34***	0.11***	1.00									
Deal Flow (Industry)	(6)	0.02***	0.02***	0.44***	0.18***	0.41***	1.00								
Exit Market Attract. (Country)	(7)	0.08***	0.02***	-0.05***	0.05***	-0.03***	0.11***	1.00							
Exit Market Attract. (Industry)	(8)	0.09***	0.01**	-0.03***	0.05***	-0.01*	0.05***	0.69***	1.00						
Round Number	(9)	0.04***	0.02***	-0.01	0.04***	0.03***	-0.02***	0	0	1.00					
No. of Investors	(10)	-0.01*	0.09***	0.03***	0.04***	0.20***	0.09***	-0.14***	-0.13***	0.37***	1.00				
Experience	(11)	-0.27***	-0.07***	0.05***	-0.10***	0.16***	0.06***	0.05***	0.05***	-0.03***	0.01	1.00			
First Fund	(12)	0.19***	0.30***	-0.05***	0.07***	0.06***	0.10***	-0.05***	-0.03***	0.03***	0.07***	-0.34***	1.00		
Fund Size	(13)	-0.04***	-0.27***	0.25***	0.02***	0.08***	0.17***	0.02***	0.03***	0.01**	-0.05***	0.42***	-0.19***	1.00	
Fund Age	(14)	-0.12***	0.72***	-0.22***	-0.08***	-0.07***	-0.11***	0.04***	0.03***	0.05***	0.02***	-0.08***	0.30***	-0.25***	1.00

2.4 Econometric Analysis

2.4.1 What is driving Style Drifts?

To model the likelihood of stage drifts we employ logistic regressions models for the main analysis with the different style drift dimensions as the binary dependent variable $P(\textit{Style Drift})$. Style drifts are separately analyzed for upwards stage drifts, downwards stage drifts, location drifts, and industry drifts. The general specification for all regressions in tables 2.7, 2.8, and 2.9 is:

$$\begin{aligned} P(\textit{Style Drift}_{i,s}) = \alpha &+ \beta_1 \textit{Past Performance}_i + \beta_2 \textit{MSCI World}_i + \beta_3 \textit{Fund Inflows}_i \\ &+ \beta_4 \textit{Deal Flow}_{i,s} + \beta_5 \textit{Exit Market Attractiveness}_{i,s} + \gamma \textit{Controls}_i \\ &+ \delta \textit{FE(Region}_i\textit{, Stage}_i\textit{, Industry}_i\textit{)} + u_i \end{aligned} \tag{2.1}$$

where individual deals are indexed with i and style dimension-specific variables are indexed with s. We use the explanatory variables connected to the hypotheses as well as the controls as described in section 2.3.1. Furthermore, we follow Schertler and Tykvová (2011), who study VC internationalization, in the approach of including fixed effects for the major cross-sectional characteristics of funds in our data set. For this study, this means including fund stage, fund region, and preferred industry fixed effects in the regressions to control for preferred investment style characteristics. The major benefit of this approach is that it controls for all time-invariant differences between the respective preferred style dimensions and thus the model is less likely to be subject to criticism regarding omitted variable bias or misspecification. All tables in the following report the regression coefficients, while we focus on marginal effects for better interpretation in the main text. The reported standard errors are clustered at the venture capital fund level. In unreported regressions, the results remain robust to additionally clustering the standard errors by investment year.

Stage

Table 2.7 presents the main results for stage drifts in both directions, upwards and downwards. The number of observations varies because the different stage drifts are not defined for all deals in the sample. Models (1) - (5) exclude later stage focussed funds, while models (6) - (10) exclude seed-stage focussed funds. All models exclude funds without stage focus. We first regress each explanatory variable connected to the hypothesis separately before we estimate the full regression specification. The results show that the stage drifting decision is not random. Most regressors do show opposite signs for the two different stage drifting directions, indicating that they represent vastly different investment decisions. This underscores the importance to separate upwards and downwards stage drifts in the analysis.

The results are completely in line with the prediction of **H1**. *Past performance* has a positive sign and is highly significant at the 1%-level in models (1) and (5) and has a negative sign and is significant at the 1%-level as well in models (6) and (10). Thus the notion that well-performing VCs have a higher propensity to stage drift downwards into riskier investment stages is confirmed, as well as that well-performing VCs are less likely to upward stage drift. The coefficients do also have economic significance. In particular, the coefficient of 0.451 in model (5) translates into a marginal effect of 0.068, which means a one standard deviation increase in *Past Performance* leads to a 1.5 percentage points higher probability of downwards stage drifting. Taking the performance ranking of fund tournaments into consideration, this also corresponds to a 3.7 percentage points higher probability of downwards stage drifting for a high performing VC at the 90^{th} percentile compared to a low performing VC at the 10^{th} percentile of the *Past Performance* distribution. The inverse does also hold in the case of upwards stage drifts. Well-performing funds have a lower propensity to drift upwards into less risky investment stages. The coefficient (-0.338) in model (10) translates into a marginal effect of -0.059, i.e. a one standard deviation increase in *Past Performance* decreases the probability of an upward stage drift by 1.3 percentage points. Looking at the same percentiles of low and high-performing VCs this corresponds to a 3.1 percentage points lower probability of downwards stage drifting for a well-performing VC.

Turning to **H2** and the effect of market conditions on risk-taking attitude, on the one hand, there is support for the hypothesis that riskier drifts are more likely when public markets are hot in models (2) and (5), in which *MSCI World* has a positive sign and high significance. A one standard deviation change in the *MSCI World* variable in model (5) corresponds to a 5.0 percentage point higher probability of stage drifting downwards. On the other hand, however, there is only very weak support for the hypothesis that booming public markets lead to a decreased probability of upward stage drifting. While model (7) has a negative sign for *MSCI World*, the statistical significance is very low (p-value = 0.089) and the significance completely vanishes in model (10). These two observations together imply that hot public markets are related to a higher probability of investing in riskier stage drifts, but that they do not significantly decrease the probability of investing in less risky later development stages. This is in line with the model of

Inderst and Müller (2004), which predicts that VCs are willing to accept higher levels of information asymmetry and thus more risk in hot public markets.

Next, we turn to variables connected to **H3a** and **H3b**, which predict drifts, irrespective of the associated investment risk, to be more likely when competition is high. *Fund Inflows* is highly significant at the 1%-level in all models, but while the expected positive sign can be observed for the case of upward stage drifts, interestingly, *Fund Inflows* exhibits a negative coefficient for downward stage drifts. A one standard deviation change of *Fund Inflows* corresponds to a 3.4 percentage points lower probability of stage drifting downwards and to a 4.4 percentage points higher probability of stage drifting upwards in models (5) and (10), respectively. This pattern shows that VCs are more likely to drift upwards but less likely to drift downwards when competition in the form of 'money chasing deals', i.e. high capital inflows, is high and therefore only partly supports **H3a** that predicts a higher probability of drifts in both dimensions.

The preference to rather drift upwards when competition increases is also supported by the non-significant coefficient of *Deal Flow* in the case of downward stage drifts (0.046, p-value = 0.377) and the significant coefficient with a negative sign in the case of upward stage drifts (-0.243, p-value = 0.000). A one standard deviation increase of *Deal Flow* corresponds to a decrease of the probability of stage drifting upwards by 2.5 percentage points. Thus, **H3b** can be confirmed for upward stage drifts only.

To address concerns that the results might be biased because we separate the analysis for upwards and downwards stage drifts, we conduct one more regression as a robustness check with the two discrete outcome possibilities in one model. Model (11) in table 2.7 shows the results of a multinomial logistic regression with no drift as the base outcome, where the two stage drifting directions are estimated as alternative outcomes in one model. As early-stage funds can drift in both stage directions, the sample only consists of all investments of early-stage focussed funds. The results are qualitatively and quantitatively consistent with the results presented in the individual logistic regressions of models (1) - (10). In contrast to the logistic regression models, this approach shows weak significance (p-value = 0.054) for *Deal Flow*, lending some more support to **H3b** in connection with downward stage drifts.

Table 2.7.: Determinants of Stage Drifts

This table reports the results of logistic regressions studying the determinants of downward stage drift in models (1) - (5), upward stage drifts in models (6) - (10), and the results of a multinomial logistic regression studying downward and upward stage drifts combined in model (11). The sample is at the deal level covering 31,521 deals. The dependent variable for the logistic regressions is a dummy variable indicating whether the investment in the portfolio company in question represents a downward stage drift or an upward stage drift for the venture capital fund with one, and zero otherwise. For the multinomial logistic regression, the base outcome is no drift. The sample consists of all first-time investments made by venture capital funds in portfolio companies. Funds without stage focus or seed focus are excluded from the sample in models (1) - (5), as downward stage drift is not defined for those cases. Funds without stage focus or later stage focus are excluded from the sample in models (6) - (10), as upward stage drift is not defined for those cases. Model (11) only includes funds with early-stage focus, because they can drift in both directions. *Past Performance* is the share of successful exits of all investments of the venture capital firm minus the industry average performance in the 5 years preceding the investment. *MSCI World* is the change of the MSCI World Index between the investment and the fund's founding date. *Fund Inflows* is the inflation corrected sum of region-specific inflow of capital into new funds in the two years preceding the investment. *Deal Flow (Stage)* is the number of deals in the preferred style in the year preceding the investment divided by the number of VCs active in the respective style in the same time interval. *Round Number* is the numeric sequence of the investment round. *No. of Investors* is the number of funds participating in the investment round. *Experience* is the natural logarithm of the number of prior investments by the venture capital firm. *First Fund* is a dummy variable indicating whether a fund is the first fund of the venture capital firm. *Fund Size* is the natural logarithm of the fund's size in 1985-Dollar. *Fund Age* is the age of the venture capital fund at the time of investment. All regressions are estimated with a constant term, fund stage, fund industry, and fund region fixed effects (not reported). Robust standard errors clustered at the venture capital fund level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	Stage Drift Down					Stage Drift Up					Down	Up
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	
Past Performance	0.580***				0.451***	-0.353***				-0.338***	0.385**	-0.315***
	(0.135)				(0.134)	(0.119)				(0.115)	(0.149)	(0.113)
MSCI World		0.275***			0.341***		-0.079*			-0.047	0.434***	0.064
		(0.049)			(0.053)		(0.046)			(0.048)	(0.063)	(0.05)
Fund Inflows			-0.180***		-0.192***			0.165***		0.221***	-0.206***	0.129***
			(0.028)		(0.031)			(0.025)		(0.030)	(0.034)	(0.032)
Deal Flow (Stage)				-0.055	-0.046				-0.092**	-0.243***	-0.129*	-0.121**
				(0.042)	(0.052)				(0.042)	(0.049)	(0.067)	(0.051)
Round Number	-0.835***	-0.827***	-0.830***	-0.834***	-0.829***	0.936***	0.932***	0.939***	0.933***	0.938***	-0.528***	0.826***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.035)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.045)	(0.029)
No. of Investors	-0.018	-0.025**	-0.016	-0.018	-0.020*	0.055***	0.057***	0.054***	0.057***	0.059***	-0.012	0.049***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.009)
Experience	0.180***	0.143***	0.135***	0.151***	0.142***	-0.161***	-0.141***	-0.125***	-0.147***	-0.140***	0.133***	-0.101***
	(0.030)	(0.028)	(0.029)	(0.029)	(0.029)	(0.025)	(0.024)	(0.023)	(0.024)	(0.024)	(0.032)	(0.024)
First Fund	0.226***	0.234***	0.291***	0.295***	0.191**	-0.072	-0.102	-0.126	-0.108	-0.051	0.145	-0.081
	(0.083)	(0.081)	(0.084)	(0.083)	(0.084)	(0.091)	(0.091)	(0.090)	(0.090)	(0.088)	(0.107)	(0.086)
Fund Size	-0.128***	-0.114***	-0.108***	-0.127***	-0.092***	0.114***	0.108***	0.092***	0.113***	0.088***	-0.061**	0.081***
	(0.023)	(0.023)	(0.024)	(0.024)	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)	(0.021)	(0.025)	(0.023)
Fund Age	-0.017	-0.071***	-0.029**	-0.025**	-0.084***	0.033***	0.048***	0.045***	0.034***	0.043***	-0.108***	0.019
	(0.011)	(0.014)	(0.012)	(0.011)	(0.015)	(0.010)	(0.012)	(0.010)	(0.010)	(0.013)	(0.017)	(0.012)
Region Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Stage Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	19,929	19,929	19,929	19,929	19,929	18,069	18,069	18,069	18,069	18,069	16,658	
Pseudo R^2	0.1308	0.1326	0.1332	0.1292	0.1395	0.2226	0.2222	0.2251	0.2223	0.2279	0.1627	

Location

In table 2.8 the results of logistic regressions analyzing location drifts are shown. The pattern that emerges is qualitatively very similar to the results for downward stage drifts in table 2.7 Again, *Past Performance* has a positive sign and is statistically significant, albeit weaker than in the case of stage drifts. The p-values are 0.038 and 0.094 for models (1) and (6), respectively. The marginal effect in model (5) is 0.030 which means a one standard deviation increase in *Past Performance* increases the probability of a location drift by only 0.6 percentage points, whereas the difference in probability of a low (10th percentile) vis-à-vis a well (90th percentile) performing VC is 1.6 percentage points. These values are considerably smaller than in the case of downward stage drift, which could mean that *Past Performance* does play a less important role in this drifting decision in comparison. However, the coefficients are not directly comparable, because the baseline probability of a drift occurring is much lower for location drifts.[12] *MSCI World* has a positive influence on location drifts in models (2) and (6). The coefficient of 0.231 translates into a marginal effect of 0.017. A one standard deviation change in *MSCI World* increases the probability of a location drift by 1.7 percentage points. Turning to *Fund Inflows* and **H3a**, the coefficients do have the expected positive sign, however, they are not statistically significant in both cases. In model (6) *Fund Inflows* has a p-value of 0.121, which is at least some very weak indication that capital supply plays a role in location drifts. The effect of *Deal Flow* is as predicted by **H3b**. The marginal effect in model (6) is -0.009, which means a one standard deviation increase in *Deal Flow* decreases the probability of a location drift by 2.4 percentage points. Finally, for location drifts, we also include *Exit Market Attractiveness* to test **H4** that predicts that lower than usual exit market attractiveness in the home country might lead VCs to chase returns at another location. The coefficients do exhibit a positive sign, which is the opposite of what **H4** hypothesized, however, the coefficients are not significant.

We run a regression with an alternative definition for location drift in model (7) as a robustness check. This alternative definition classifies only out-of-region investments as a location drift. For the sample, this means that investments of a European fund within Europe are not classified as a location drift. This narrower definition consequently only captures location drifts that also entail a large geographical distance between VC and portfolio company. The results are robust to this alternative definition. All coefficients have the same signs and magnitude. *Fund Inflows* does gain statistical significance

[12]In relative terms, the probability of a location drift is 17.8% higher for a well-performing vis-à-vis a low-performing VC. This relative effect size is very close to the relative effect size in the case of downward stage drifts (17.4%).

Table 2.8.: Determinants of Location Drifts

This table reports the results of logit regressions studying the determinants of location drifts. The sample is at the deal level covering 31,521 deals. The dependent variable in models (1) - (6) is a dummy variable indicating whether the investment in the portfolio company in question represents a location drift (defined as country difference) for the venture capital fund with one, and zero otherwise. In model (7) an alternative location drift definition is used for the dependent variable, where only intra-region drifts are considered. The sample consists of all first-time investments made by venture capital funds in portfolio companies. *Past Performance* is the share of successful exits of all investments of the venture capital firm minus the industry average performance in the 5 years preceding the investment. *MSCI World* is the change of the MSCI World Index between the investment and the fund's founding date. *Fund Inflows* is the inflation corrected sum of region-specific inflow of capital into new funds in the two years preceding the investment. *Deal Flow (Country)* is the number of deals in the preferred style in the year preceding the investment divided by the number of VCs active in the respective style in the same time interval. *Exit Market Attract. (Country)* is the fraction of IPOs of all successful exits in the fund's home country in the year preceding the investment minus the three-year moving average. *Round Number* is the numeric sequence of the investment round. *No. of Investors* is the number of funds participating in the investment round. *Experience* is the natural logarithm of the number of prior investments by the venture capital firm. *First Fund* is a dummy variable indicating whether a fund is the first fund of the venture capital firm. *Fund Size* is the natural logarithm of the fund's size in 1985-Dollar. *Fund Age* is the age of the venture capital fund at the time of investment. All regressions are estimated with a constant term, fund stage, fund industry, and fund region fixed effects (not reported). Robust standard errors clustered at the venture capital fund level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Past Performance	0.482**					0.398*	0.458*
	(0.232)					(0.238)	(0.249)
MSCI World		0.194***				0.231***	0.206***
		(0.069)				(0.072)	(0.071)
Fund Inflows			0.034			0.067	0.089*
			(0.041)			(0.043)	(0.050)
Deal Flow (Country)				-0.086**		-0.119***	-0.111***
				(0.034)		(0.035)	(0.036)
Exit Market Attract. (Country)					0.243	0.249	0.595***
					(0.171)	(0.182)	(0.214)
Round Number	0.047***	0.057***	0.053***	0.043***	0.050***	0.047***	0.020
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.015)
No. of Investors	-0.031**	-0.036**	-0.033**	-0.026*	-0.031**	-0.028*	-0.025
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.018)
Experience	0.051	0.019	0.028	0.020	0.022	0.044	0.065
	(0.042)	(0.041)	(0.041)	(0.040)	(0.040)	(0.042)	(0.043)
First Fund	0.219	0.233	0.269	0.294*	0.275	0.225	0.174
	(0.175)	(0.172)	(0.173)	(0.173)	(0.173)	(0.174)	(0.183)
Fund Size	0.288***	0.303***	0.286***	0.288***	0.293***	0.287***	0.214***
	(0.054)	(0.053)	(0.053)	(0.054)	(0.053)	(0.055)	(0.057)
Fund Age	0.015	-0.025	0.011	0.005	0.009	-0.033*	-0.024
	(0.013)	(0.017)	(0.013)	(0.013)	(0.013)	(0.018)	(0.019)
Region Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Industry Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Stage Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Observations	31,521	31,521	31,521	31,521	31,521	31,521	31,521
Pseudo R^2	0.1568	0.1576	0.1557	0.1575	0.1558	0.1621	0.0764

at the 10%-level in this specification, which implies that increased competition on the capital supply side does increase the probability of intra-region location drifts. The most noteworthy difference is the high significance of the coefficient of *Exit Market Attractiveness*, which still has the unexpected positive sign. One explanation for this positive sign might be, that VCs invest abroad more, to exploit the overly attractive local exit market by taking foreign portfolio companies public or selling them at home.[13]

Industry

Table 2.9 reports the results of the main analysis of industry drifts in models (1) - (6). As the univariate analysis has already indicated, the effect of *Past Performance* is contrary to what **H1** predicts. The negative sign of the coefficient in models (1) and (6) means that lower-performing VCs are more likely to conduct industry drifts. The marginal effect of *Past Performance* in model (6) is -0.132, or in other words, a one standard deviation increase in *Past Performance* decreases the probability of an industry drift by 2.8 percentage points. The comparison of a low (10th percentile) vis-à-vis a well (90th percentile) performing VC shows a 7.1 percentage point lower probability for the well-performing VC. These results clearly show that industry drifts do differ considerably from the other two drift dimensions. Potential explanations for the reversed sign are that poorly performing VCs might have worse access to high-quality deals in their preferred industries or actively reconsider their industry focus due to lack of success in the originally preferred industries and thus do need to drift. Even though **H1** cannot be confirmed, models (2) and (6) show the same positive sign for the highly significant coefficients for *MSCI World* as downward stage drifts and location drifts do. The effect of a one standard deviation increase of *MSCI World* in model (6) corresponds to a 3.6 percentage point increase of the probability of an industry drift. Just as in the case of location drifts, there is no significance for the coefficients of *Fund Inflows*, which means there is no evidence in support of **H3a**. **H3b** can be confirmed consistently again in the case of industry drifts. *Deal Flow* has a negative sign and is highly significant. A one standard deviation increase in *Deal Flow* in model (6) leads to a 3.4 percentage point decreased probability of an industry drift. There is also support for **H4** in the case of industry drifts. *Exit Market Attractiveness* has the predicted negative sign and is highly significant. The marginal effect in model (6) is -0.134 which means a decrease of *Exit*

[13] Tykvová (2018a) finds evidence in support of this explanation. Exits abroad are more likely for portfolio companies with international VCs among the investors, especially if the portfolio company's home country has lower legal framework quality. Due to the stricter definition of location drifts in model (7), the fraction of investments into companies outside of Europe and the US is much higher than for the main location drift definition, which increases the fraction of location drifts into countries with a low legal framework quality.

Market Attractiveness by one standard deviation increases the probability of an industry drift by 2.1 percentage points. This is in line with **H4** which predicts that when the IPO rate within the preferred industries is lower than usual as defined in section 2.3.1 industry drifts are more likely.

To address concerns, that the main definition of industry drifts is too broad and classifies too many investments as industry drift, we introduce two alternative industry drift definitions in models (7) and (8) serving as robustness checks. As some funds might be specialized in more than two industries, the alternative definitions are much more narrow to ensure that the investments are not in the fund's preferred industry style and represent investments outside the area of specialization. In model (7) we use the first alternative definition for industry drift as the dependent variable, which only treats investments into industries in which the fund has had no more than one prior investment as a drift. The second alternative definition in model (8) categorizes all investments in which the VC firm has not had more than one investment in the last six years as an industry drift. Both definitions should capture the increased risk-taking attitude, by focussing on the outliers.

The results are qualitatively and quantitatively very similar to the main analysis. A noteworthy difference is the highly significant positive coefficient for *Fund Inflows* in model (7). While in line with the prediction of **H3a**, this single significant result is still contrasted by the non-significance in all other models. Furthermore, *Exit Market Attractiveness* loses its significance in both alternative specifications. This might indicate, that VCs only invest in industries, in which they have some prior experience, when exit markets are cooler than usual in their preferred industries, while they are not more likely to chase returns in industries, in which they have not invested several times before.

Table 2.9.: Determinants of Industry Drifts

This table reports the results of logistic regressions studying the determinants of industry drifts. The sample is at the deal level covering 31,521 deals. The dependent variable in models (1) - (6) is a dummy variable indicating whether the investment in the portfolio company in question represents an industry drift for the venture capital fund based on the main definition with one, and zero otherwise. In model (7) industry drift is defined alternatively only for investments into industries in which the fund has had no more than one prior investment. Model (8) uses a second alternative definition, where only industries in which the VC firm has not had more than one investment in the last six years are defined as an industry drift. The sample consists of all first-time investments made by venture capital funds in portfolio companies. *Past Performance* is the share of successful exits of all investments of the venture capital firm minus the industry average performance in the 5 years preceding the investment. *MSCI World* is the change of the MSCI World Index between the investment and the fund's founding date. *Fund Inflows* is the inflation corrected sum of region-specific inflow of capital into new funds in the two years preceding the investment. *Deal Flow (Industry)* is the number of deals in the preferred style in the year preceding the investment divided by the number of VCs active in the respective style in the same time interval. *Exit Market Attract. (Industry)* is the fraction of IPOs of all successful exits in the fund's preferred investment industries in the year preceding the investment minus the three-year moving average. *Round Number* is the numeric sequence of the investment round. *No. of Investors* is the number of funds participating in the investment round. *Experience* is the natural logarithm of the number of prior investments by the venture capital firm. *First Fund* is a dummy variable indicating whether a fund is the first fund of the venture capital firm. *Fund Size* is the natural logarithm of the fund's size in 1985-Dollar. *Fund Age* is the age of the venture capital fund at the time of investment. All regressions are estimated with a constant term, fund stage, fund industry, and fund region fixed effects (not reported). Robust standard errors clustered at the venture capital fund level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past Performance	-0.557***					-0.575***	-0.714***	-0.924***
	(0.089)					(0.090)	(0.085)	(0.092)
MSCI World		0.106***				0.163***	0.170***	0.102***
		(0.029)				(0.031)	(0.033)	(0.032)
Fund Inflows			-0.015			-0.002	0.079***	0.013
			(0.017)			(0.019)	(0.020)	(0.022)
Deal Flow (Industry)				-0.075***		-0.099***	-0.176***	-0.171***
				(0.014)		(0.015)	(0.017)	(0.020)
Exit Market Attract. (Industry)					-0.683***	-0.584***	-0.098	-0.044
					(0.102)	(0.103)	(0.116)	(0.117)
Round Number	-0.007	-0.007	-0.010	-0.014*	-0.007	-0.007	-0.007	-0.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)
No. of Investors	-0.000	-0.000	0.002	0.005	-0.003	-0.001	-0.017***	-0.047***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Experience	0.066***	0.093***	0.094***	0.093***	0.101***	0.062***	-0.132***	-0.711***
	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.023)
First Fund	-0.052	-0.128**	-0.105*	-0.081	-0.105*	-0.056	-0.402***	-0.176***
	(0.063)	(0.064)	(0.063)	(0.064)	(0.064)	(0.065)	(0.064)	(0.058)
Fund Size	-0.042**	-0.037**	-0.042**	-0.041**	-0.045***	-0.027	-0.136***	-0.089***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Fund Age	0.014***	0.001	0.018***	0.014***	0.021***	-0.015**	-0.110***	0.036***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.010)	(0.009)
Region Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Industry Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Stage Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	31,521	31,521	31,521	31,521	31,521	31,521	31,521	31,521
Pseudo R^2	0.0575	0.0562	0.0555	0.0567	0.0572	0.0617	0.1141	0.1338

Risk-taking Plausibility Check and Discussion of Results

To further strengthen our arguments regarding the relationship of style drifts and risk-taking laid out in section 2.2.1 we conduct an additional plausibility check to confirm that style drifts do bear risk-taking information. In table 2.10 we include *Uncertainty Avoidance* as additional control variable in the full model specifications for each style drift dimension. The variable cannot be included in the main analysis due to the presence of region fixed effects that control for unobserved region-specific factors. As *Uncertainty Avoidance* is constant over time and highly correlated geographically, including both, region fixed effects and *Uncertainty Avoidance*, in the same model would lead to econometric issues. *Uncertainty Avoidance* is one of several cultural dimensions described in Hofstede (2001) capturing informal institutions across countries. Societies with a higher level of the Hofstede uncertainty avoidance index exhibit lower willingness to take risks and have a greater fear of failure, while low levels of uncertainty avoidance are associated with a higher willingness to take risks (Hofstede 2001). We build on earlier work analyzing how uncertainty avoidance is related to risk-taking in venture capital investments. Cumming et al. (2016a) show that there is a negative relationship between uncertainty avoidance and VCs' willingness to invest in risky cleantech investments. Thus, we expect to find the same negative relationship between *Uncertainty Avoidance* and riskier style drifts in table 2.10. The analysis confirms the expected negative relationship between *Uncertainty Avoidance* and risky style drifts in models (1) - (3) for both stage drifts and location drifts. However, we do not find any statistically significant relationship with industry drifts in model (4), which indicates that industry drifts might not be perceived as riskier investments. The results of the plausibility check are fully compatible with the findings of the main analysis.

Based on the discussion about a potential agency conflict between LPs and GPs and the distinction between deliberate risk-taking and risk-taking out of necessity in section 2.2.3 and the plausibility check above the results shed light on the question whether style drifts by the GP are in the best interest of the LP. With regard to the potential agency conflict statistically significant effects for *Past Performance* and *MSCI World* in line with **H1** and **H2** imply that VCs alter the risk profile of a fund deliberately to increase their potential carried interest compensation. The results across all style drift dimensions indicate that *Past Performance* is a relevant factor influencing style drifting. The analyses for stage drifts and location drifts, by and large, confirm the hypothesis that well-performing VCs are more prone to increase their risk-taking attitude. Additionally, comparing the results for the hypothesis that riskier drifts are more likely when public markets perform well across style drift dimensions, show consistent results. VCs have a higher risk-taking appetite when public markets are hot. This is in line with the findings of Buzzacchi et al. (2015), who also find booming public market conditions to affect risk-taking positively. This means that GPs alter the risk-return profile of their fund deliberately to maximize their own compensation potential when they have confidence that this will not negatively affect their ability to raise a follow-on fund. Under the assumption that LPs allocate their capital into a fund with the expectation of a specific risk-return profile, this deliberate alteration of the risk-return profile is not in the LP's best interest. The case of industry drifts, however, differs from stage and location drifts and indicates the opposite effect of *Past Performance* on the probability of a drift. This might indicate that industry drifts might be in the best interest of LPs. There are two alternative explanations for the observation that poorly performing VCs are more likely to conduct industry drifts. As an investment decision is a two-sided matching process, entrepreneurs might refrain from seeking an investment from a poorly performing VC. In turn, this might make it necessary for poorly performing VCs to then strain further from their industry comfort zones. Alternatively, the VCs themselves might actively abandon their prior focus, when they conclude that the chosen industry focus is the reason for the lack of success. These explanations are more in accordance with the results for drifts out of necessity. When GP drift in their style out of necessity, this should be in the best interest of the LP, because the alternatives would be to either not invest the fund's capital at all, or to accept unjustifiably high price tags to attract high-quality companies in the preferred style, or even to knowingly invest into low-quality companies without much potential.

Regarding **H3a** and **H3b**, on the one hand, *Deal Flow* is consistently negatively related to the probability of style drifts, which indicates that necessity to drift is an important factor. On the other hand, the effect of increased *Fund Inflows*, i.e. competition on the supply side of capital, is only significant in select specifications. The hypothesis, that VCs are more likely to drift in every style dimension due to competition cannot fully be confirmed. In particular, the results for both directions of stage drifts indicate, that an abundance of capital inflows leads to more upward stage drifts and fewer downward stage drifts. One explanation for this observation is that drifting into lower stages typically involves smaller investment amounts. Thus, if a lot of capital is available, VCs favor drifting into later stages, where they can invest larger amounts at once. This is also reconcilable with Bubna et al. (2020), who find that the amount of a fund's uninvested capital creates pressure to invest all committed capital in time. Finally, the hypothesis that VCs chase returns via style drifts, can only be confirmed for industry drifts. However, the statistical significance vanishes in the alternative specifications even in this case.

Table 2.10.: Relationship of Uncertainty Avoidance and Style Drifts

This table reports the results of logistic regressions studying the relationship of style drifts and uncertainty avoidance. The sample is at the deal level covering 31,521 deals. The dependent variable is a dummy variable indicating whether the investment in the portfolio company in question represents a style drift in the indicated style dimension for the venture capital fund with one, and zero otherwise. The sample consists of all first time investments made by venture capital funds in portfolio companies. *Uncertainty Avoidance* is the Hofstede uncertainty avoidance index. *Past Performance* is the share of successful exits of all investments of the venture capital firm minus the industry average performance in the 5 years preceding the investment. *MSCI World* is the change of the MSCI World Index between the investment and the fund's founding date. *Fund Inflows* is the inflation corrected sum of region specific inflow of capital into new funds in the two years preceding the investment. *Deal Flow* is the number of deals in the preferred style in the year preceding the investment divided by the number of VCs active in the respective style in the same time interval. *Exit Market Attract.* is the fraction of IPOs of all successful exits in the fund's preferred style in the year preceding the investment minus the three-year moving average. *Round Number* is the numeric sequence of the investment round. *No. of Investors* is the number of funds participating in the investment round. *Experience* is the natural logarithm of the number of prior investments by the venture capital firm. *First Fund* is a dummy variable indicating whether a fund is the first fund of the venture capital firm. *Fund Size* is the natural logarithm of the fund's size in 1985-Dollar. *Fund Age* is the age of the venture capital fund at the time of investment. All regressions are estimated with a constant term, fund stage, and fund industry fixed effects (not reported). Robust standard errors clustered at the venture capital fund level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
	Stage Down	Stage Up	Location	Industry
Uncertainty Avoidance	-0.266*	0.369**	-0.458*	0.157
	(0.154)	(0.172)	(0.255)	(0.127)
Past Performance	0.568***	-0.521***	0.166	-0.614***
	(0.134)	(0.120)	(0.232)	(0.090)
MSCI World	0.362***	-0.090*	0.257***	0.156***
	(0.056)	(0.052)	(0.072)	(0.031)
Fund Inflows	-0.138***	0.110***	0.096*	-0.024
	(0.030)	(0.030)	(0.054)	(0.018)
Deal Flow	-0.086*	-0.154***	-0.231***	-0.091***
	(0.051)	(0.052)	(0.027)	(0.015)
Exit Market Attract.			0.682***	-0.599***
			(0.227)	(0.103)
Round Number	-0.831***	0.927***	0.009	-0.008
	(0.035)	(0.027)	(0.015)	(0.008)
No. of Investors	-0.015	0.046***	-0.022	-0.003
	(0.011)	(0.009)	(0.018)	(0.005)
Experience	0.182***	-0.218***	-0.001	0.046**
	(0.028)	(0.024)	(0.040)	(0.018)
First Fund	0.205**	-0.094	0.195	-0.068
	(0.084)	(0.091)	(0.183)	(0.064)
Fund Size	-0.095***	0.089***	0.202***	-0.027
	(0.023)	(0.022)	(0.056)	(0.017)
Fund Age	-0.092***	0.055***	-0.040**	-0.012*
	(0.015)	(0.013)	(0.019)	(0.007)
Region Fixed Effects	no	no	no	no
Industry Fixed Effects	yes	yes	yes	yes
Stage Fixed Effects	yes	yes	yes	yes
Observations	19,929	18,083	31,521	31,521
Pseudo R^2	0.1367	0.2182	0.0719	0.0611

2.4.2 What are the Performance Implications of Investment Style Drifts?

Individual Investment Success

As a logical next step of the analysis, we are interested in how style drifts affect the performance of individual investments. If style drifts are in fact reflections of the risk-taking attitude of the GP, riskier drifts should lead to a lower probability of a successful exit for the VC fund. Thus, we run eight separate probit[14] regressions for each individual style drift dimension and several aggregate style drift variables in model (1) - (8) in table 2.11 with *Success* as the binary dependent variable with the following model specification

$$P(Success_i) = \alpha + \beta Style\ Drift_i + \gamma Controls_i + \delta FE(Industry_i,\ Year_i) + u_i \qquad (2.2)$$

where individual investments are indexed with i. $Style\ Drift_i$ is a vector of the different individual and aggregate style drift variables. $Controls_i$ is a vector of controls. We control for the VC's experience, the amount invested in the portfolio company in the investment round, whether the deal was syndicated, public market conditions in the exit year[15], and the legal system quality of the portfolio company's country. The *Legal System Quality* variable is an index based on the data in the seminal work of La Porta et al. (1998) that we construct with the methodology described in Berkowitz et al. (2003). We include it because e.g. Cumming et al. (2006) and Tykvová (2018a) show that a higher quality legal system in the portfolio company's country is associated with a higher likelihood for successful exits. Additionally, we also include *Past Performance* to rule out that the drift variables simply proxy for omitted performance persistence. Furthermore, we include portfolio company industry fixed effects and year of investment fixed effects.[16]

[14] As we later also employ recursive bivariate probit models (without a logistic counterpart) to address self-selection concerns, we want to stay consistent within this part of the analysis and use probit regressions instead of logistic regressions here. Using a logistic link function in this step of the analysis does not change the results.

[15] To calculate the variable capturing public market conditions in the exit year for portfolio companies that have not been successfully exited, we rely on the theoretical exit date as discussed in section 2.3.1 that we also use for the calculation of *Past Performance*.

[16] Results stay qualitatively the same when we include country fixed effects instead of *Legal System Quality*.

Table 2.11.: Effect of Style Drifts on Individual Investment Success

This table reports the results of probit regressions studying the effect of style drifts on individual exit success. The sample is at the deal level covering 31,521 deals. The dependent variable is a dummy variable indicating whether the investment in the startup company in question has been successfully exited via an IPO or trade sale with one, and zero otherwise. The sample consists of all first-time investments made by venture capital funds in portfolio companies. Funds without stage focus or seed focus are excluded from the sample in models (1) and (5) and (7), as downward stage drift is not defined for those cases. Funds without stage focus or later stage focus are excluded from the sample in model (2), as upward stage drift is not defined for those cases. *Stage Drift Down*, *Stage Drift Up*, *Location Drift*, and *Industry Drift* are dummies indicating a style drift in the respective dimension with one, and zero otherwise. *Drift Score (excl. Stage Up)* is the number of style drifts per portfolio company, not counting (less risky) upwards stage drifts. *1 Drift*, *2 Drifts*, *3 Drifts* is a set of dummy variables equal to one when *Drift Score (excl. Stage Up)* is equal to the respective number of drifts, and zero otherwise. *Experience* is the natural logarithm of the number of prior investments by the venture capital firm. *Invested Amount* is the dollar amount invested in the portfolio company. *Syndication* is a dummy indicating whether a deal is syndicated. *MSCI World (Exit Year)* is the return of the MSCI World in the exit year. *Legal System Quality* is an index measuring the legal system quality of the portfolio company's country. *Past Performance* is the share of successful exits of all investments of the venture capital firm minus the industry average performance in the 5 years preceding the investment. All regressions are estimated with a constant term portfolio company industry fixed effects and year of investment fixed effects (not reported). Robust standard errors clustered at the venture capital fund level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Stage Drift Down	-0.160***							
	(0.024)							
Stage Drift Up		0.186***						
		(0.022)						
Location Drift			-0.123***					
			(0.031)					
Industry Drift				-0.030*				
				(0.016)				
Drift Score (excl. Stage Up)					-0.090***	-0.079***		
					(0.014)	(0.012)		
1 Drift							-0.065***	-0.060***
							(0.021)	(0.017)
2 Drifts							-0.185***	-0.168***
							(0.031)	(0.026)
3 Drifts							-0.342***	-0.310***
							(0.118)	(0.118)
Experience	0.077***	0.089***	0.064***	0.065***	0.074***	0.066***	0.074***	0.066***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
Invested Amount	0.023***	0.018***	0.026***	0.026***	0.024***	0.025***	0.024***	0.025***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Syndication	0.330***	0.336***	0.352***	0.357***	0.329***	0.350***	0.328***	0.349***
	(0.028)	(0.030)	(0.022)	(0.022)	(0.028)	(0.022)	(0.028)	(0.022)
MSCI World (Exit Year)	0.528***	0.506***	0.612***	0.612***	0.526***	0.615***	0.527***	0.615***
	(0.096)	(0.103)	(0.078)	(0.078)	(0.096)	(0.078)	(0.096)	(0.078)
Legal System Quality	0.054***	0.060***	0.044***	0.060***	0.040***	0.050***	0.039***	0.049***
	(0.011)	(0.012)	(0.009)	(0.008)	(0.011)	(0.008)	(0.011)	(0.009)
Past Performance	0.367***	0.334***	0.352***	0.348***	0.344***	0.345***	0.345***	0.346***
	(0.053)	(0.055)	(0.042)	(0.042)	(0.053)	(0.042)	(0.053)	(0.042)
Industry Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	19,929	18,083	31,521	31,521	19,929	31,521	19,929	31,521
Pseudo R^2	0.0850	0.0919	0.0873	0.0873	0.0840	0.0876	0.0841	0.0876

The controls show the expected signs in all model specifications. All six reported control variables have a positive sign and are statistically significant, i.e. more experienced VCs, syndicated deals, higher investment amounts, favorable public market conditions in the year of the exit, a better legal system, and high performance are associated with a higher probability of a successful exit. The results of this simple probit model are completely in line with **H5**. As expected, downward stage drifts have a negative effect on the successful exit probability and are highly statistically significant. Specifically, the effect of *Stage Drift Down* corresponds to a 5.8 percentage points lower exit probability. This fully supports the notion that downwards stage drifts are associated with higher investment risk. Turning to upward stage drifts, the very opposite effect is documented. The coefficient in model (2) is highly significant and has a positive sign. The effect of *Stage Drift Up* is a 6.7 percentage points higher probability of a successful exit. The coefficient of *Location Drift* is also negative and significant at the 1%-level. More specifically, the effect of *Location Drift* corresponds to a 4.5 percentage points lower probability of a successful exit. *Industry Drifts* shows a negative sign with significance at the 10%-level. The effect of an industry drift corresponds to a 1.1% lower success probability. Besides the effect of single drift dimensions, we are also interested in the question of whether investments that represent multiple drifts are worse than individual drifts. In models (5) and (6), we use *Drift Score (excl. Stage Up)* in the regressions. This count variable can range from 0 to 3 and is constructed as the sum of the three risky style drift dummies, only excluding *Stage Drift Up* because of its opposite risk-taking characteristic. It can be clearly observed that the probability of a successful exit decreases monotonically with an increase of *Drift Score (excl. Stage Up)* because of the highly significant negative coefficient. If an investment represents several risky style drifts, each additional style drift decreases the success probability by 3.2 percentage points. This finding can be confirmed and further detailed in models (7) and (8), where we employ a set of dummies derived from *Drift Score (excl. Stage Up)* to measure the effects of multiple drifts more granularly. The dummy analysis reveals that the success probability does not decrease linearly. The effect sizes of *1 Drift*, *2 Drifts*, and *3 Drifts* correspond to a 2.4, 6.7, and 12.4 percentage points decrease of the success probability, respectively. So far, the analysis does not consider potential endogeneity problems. The rationale behind using style drift as an explanatory variable for exit success, i.e. implying causality by using style drifts as independent variables in models (1) - (4) in table 2.11, is mainly based on the fact that exit events usually are observed multiple years after the decision whether or not to style drift takes place. However, given that the probability of style drifting is not random and most likely unobserved confounders are impacting both, style drift and exit success, simultaneously the estimated independent regression models might suffer from

Table 2.12.: Effect of Style Drifts on Individual Investment Success Controlling for Endogeneity

This table reports the results of bivariate recursive probit regressions studying the effect of style drifts on individual exit success. The sample is at the deal level covering 31,521 deals. The dependent variable in the outcome equation is a dummy variable indicating whether the investment in the startup company in question has been successfully exited via an IPO or trade sale with one, and zero otherwise. The dependent variable in the outcome equation is the respective style drift variable. The sample consists of all first-time investments made by venture capital funds in portfolio companies. Funds without stage focus or seed focus are excluded from the sample in model (1), as downward stage drift is not defined for those cases. Funds without stage focus or later stage focus are excluded from the sample in model (2), as upward stage drift is not defined for those cases. *Stage Drift Down*, *Stage Drift Up*, *Location Drift*, and *Industry Drift* are dummies indicating a style drift in the respective dimension with one, and zero otherwise. *Experience* is the natural logarithm of the number of prior investments by the venture capital firm. *Invested Amount* is the dollar amount invested in the portfolio company. *Syndication* is a dummy indicating whether a deal is syndicated. *MSCI World (Exit Year)* is the return of the MSCI World in the exit year. *Legal System Quality* is an index measuring the legal system quality of the portfolio company's country. *Past Performance* is the share of successful exits of all investments of the venture capital firm minus the industry average performance in the 5 years preceding the investment. *MSCI World* is the change of the MSCI World Index between the investment and the fund's founding date. *Fund Inflows* is the inflation corrected sum of region-specific inflow of capital into new funds in the two years preceding the investment. *Deal Flow* is the number of deals in the preferred style in the year preceding the investment divided by the number of VCs active in the respective style in the same time interval. *Exit Market Attract.* is the fraction of IPOs of all successful exits in the fund's preferred style in the year preceding the investment minus the three-year moving average. *Round Number* is the numeric sequence of the investment round. *No. of Investors* is the number of funds participating in the investment round. *Experience* is the natural logarithm of the number of prior investments by the venture capital firm. *First Fund* is a dummy variable indicating whether a fund is the first fund of the venture capital firm. *Fund Size* is the natural logarithm of the fund's size in 1985-Dollar. *Fund Age* is the age of the venture capital fund at the time of investment. All regressions are estimated with a constant term and fixed effects as indicated (not reported). Robust standard errors clustered at the venture capital fund level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)		(2)		(3)		(4)	
	Stage Down	Success	Stage Up	Success	Location	Success	Industry	Success
Stage Drift Down		-0.750***						
		(0.073)						
Stage Drift Up				0.445***				
				(0.044)				
Location Drift						-0.508***		
						(0.098)		
Industry Drift								-0.389***
								(0.103)
Experience	0.089***	0.087***	-0.089***	0.101***	0.026	0.059***	0.042***	0.062***
	(0.017)	(0.008)	(0.014)	(0.009)	(0.021)	(0.007)	(0.012)	(0.007)
Invested Amount		0.021***		0.017***		0.026***		0.025***
		(0.003)		(0.003)		(0.002)		(0.002)
Syndication		0.279***		0.299***		0.333***		0.343***
		(0.028)		(0.031)		(0.023)		(0.023)
MSCI World (Exit Year)		0.510***		0.496***		0.615***		0.602***
		(0.093)		(0.102)		(0.077)		(0.076)
Legal System Quality		0.051***		0.056***		0.052***		0.056***
		(0.011)		(0.012)		(0.009)		(0.008)
Past Performance	0.267***	0.407***	-0.209***	0.355***	0.246**	0.343***	-0.339***	0.258***
	(0.075)	(0.053)	(0.068)	(0.055)	(0.120)	(0.043)	(0.055)	(0.050)
MSCI World	0.203***		-0.029		0.117***		0.100***	
	(0.030)		(0.028)		(0.035)		(0.019)	
Fund Inflows	-0.113***		0.123***		0.051**		-0.002	
	(0.018)		(0.017)		(0.022)		(0.012)	
Deal Flow	-0.024		-0.138***		-0.058***		-0.058***	
	(0.028)		(0.029)		(0.016)		(0.010)	
Exit Market Attract.					0.153		-0.362***	
					(0.102)		(0.063)	
Round Number	-0.431***		0.534***		0.011		-0.012**	
	(0.018)		(0.015)		(0.008)		(0.006)	
No. of Investors	-0.021***		0.038***		-0.022***		-0.003	
	(0.006)		(0.005)		(0.007)		(0.003)	
First Fund	0.109**		-0.030		0.088		-0.031	
	(0.047)		(0.051)		(0.086)		(0.040)	
Fund Size	-0.056***		0.054***		0.131***		-0.019*	
	(0.013)		(0.012)		(0.025)		(0.010)	
Fund Age	-0.048***		0.024***		-0.013		-0.009**	
	(0.008)		(0.007)		(0.009)		(0.004)	
ρ	0.408***		-0.211***		0.244***		0.239***	
	(0.052)		(0.031)		(0.055)		(0.069)	
Fund Region Fixed Effects	yes	no	yes	no	yes	no	yes	no
Fund Industry Fixed Effects	yes	no	yes	no	yes	no	yes	no
Fund Stage Fixed Effects	yes	no	yes	no	yes	no	yes	no
Company Industry Fixed Effects	no	yes	no	yes	no	yes	no	yes
Investment Year Fixed Effects	no	yes	no	yes	no	yes	no	yes
Observations	19,929		18,083		31,521		31,521	

endogeneity bias. For example, the probability of a style drift and the successful exit probability might both be greater, when the portfolio company's expected performance is higher. To strengthen our results we account for the possibility of endogeneity by employing recursive bivariate probit (treatment selection) models (Heckman 1978; Greene 2018). This allows us to analyze the effect the binary endogenous drift variables have on the binary exit success variable accounting for unobserved confounders. The approach is similar to a sample selection correction, however, with this approach, we can address the self-selection into 'treatment', i.e. the decision to style drift, by estimating a system of two probit equations simultaneously. The approach allows the error terms to be correlated. Consequently, when the correlation coefficient ρ in the joint estimation model is not significant, the drift variable of interest can be treated as exogenous and thus the independent estimation of the two equations is more appropriate.

In the first equation (see equation 2.1) of the equation system style drift is the dependent variable, while it is an endogenous regressor in the second equation (see equation 2.2) with exit success as the independent variable. For the respective style drift equations, we use the same full model specifications as in the analysis in section 2.4.1. The results concerning style drift determinants discussed above are largely confirmed in the recursive bivariate probit setting. The second equation is specified analog to models (1) - (4) in table 2.11. Models (1) - (4) in table 2.12 show the results of the recursive bivariate probit approach. After accounting for endogeneity, all style drift dummies have the same sign as in the standard probit models, which confirms the general results. The marginal effect after controlling for unobserved confounders is higher compared to the standard probit models for all style drifts. The marginal effects of *Stage Drift Down*, *Stage Drift Up*, *Location Drift* and *Industry Drifts* are equal to a 26.8 percentage points decrease, a 15.9 percentage points increase, an 18.4 percentage points decrease, and 14.0 percentage points decrease of the success probability, respectively.[17] All four coefficients are significant at the 1%-level. In sum, the recursive bivariate probit models fully confirm the general results of the probit analysis and are in line with the prediction of **H5**.

Fund Success

To measure the aggregate implications of fund-level style drifts on fund performance, we follow the methodology and basic model specification used by Hochberg et al. (2007). This step of the analysis is important because portfolio effects might differ from individual

[17] We also estimate the effect size via a linear regression model with endogenous treatment effects, which uses a linear probability model to estimate the *Success* equation. The results are consistent with the main analysis and confirm the findings.

investment effects, i.e. the fund-level performance is the only performance level that is relevant for LPs who allocate capital to a fund in expectation of a certain risk-return profile. We use the fraction of a fund's successful exits, i.e. its *Exit Rate*, as the dependent variable to measure fund performance, which has been shown by Hochberg et al. (2007) to be a valid proxy for cash flow based performance measures.

$$\begin{aligned} \textit{Exit Rate}_i &= \alpha + \beta \textit{Style Drift}_i + \gamma \textit{Controls}_i \\ &\quad + \delta \textit{FE(Stage}_i\textit{, Region}_i\textit{, Vintage Year}_i\textit{)} + u_i \end{aligned} \tag{2.3}$$

Individual funds are indexed with i. *Style Drift*$_i$ is a vector if style drift related variables. *Controls*$_i$ are the same as in Hochberg et al. (2007): *Fund Sequence*, *Fund Sequence squared*, *Fund Size*, and *Fund Size squared*. Besides vintage year fixed effects used by Hochberg et al. (2007) we also add fixed effects to the model specification to control for the fund's region and the fund's investment stage focus. In table 2.13 model (1) is the baseline specification including just the controls, which we use to benchmark our model with the baseline specification of Hochberg et al. (2007). Our model's coefficients have the same sign and about the same magnitude, with a higher significance level for the coefficients and a higher overall model fit compared to Hochberg et al. (2007). We find the same positive relationship between *Fund Size* and *Fund Sequence* and the fund's overall investment success. This includes the negative sign for the squared fund size, which highlights the concave relationship between fund size and fund performance. The observation is consistent with diminishing returns to scale. Thus, for the further analysis of the impact of style drifts on fund performance, this model is suitable and in line with previous studies on fund performance in the venture capital industry.[18]

[18] In addition to the OLS approach based on Hochberg et al. (2007) described here, we also run all specifications as fractional regressions with a logistic link function and analyze marginal effects in unreported regressions. All results for the OLS results described here are qualitatively and quantitatively robust to the use of the alternative methodology.

Table 2.13.: Effect of Style Drifts on Overall Fund Investment Success

This table reports the results of OLS regressions studying the determinants of overall fund investment success. The sample is at the fund level covering 2,718 unique funds. The dependent variable is the fund's exit rate defined as the fraction of a fund's portfolio companies that have been successfully exited via an IPO or trade sale. For each fund the full investment history is included in the sample. *Stage Drift Down*, *Stage Drift Up*, *Location Drift*, and *Industry Drift* are the fractions of all investments matching the respective style drift dimension. *Drift Share* is the fraction of all investments that represent at least a drift in one style dimension. *Average Drift Score* is the average number of drifts per portfolio company. *Fund Sequence* is the position of the fund in the chronological order of all funds of the venture capital firm. *Fund Sequence squared* is the squared fund sequence. *Fund Size* is the natural logarithm of the fund's size in Dollar. *Fund Size squared* is the squared fund size. All regressions are estimated with a constant term, fund stage, fund region, and fund vintage year fixed effects (not reported). Robust standard errors clustered at the venture capital firm level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Stage Drift Down		-0.083***				-0.055*				
		(0.030)				(0.031)				
Stage Drift Up			0.090***			0.071***				
			(0.025)			(0.027)				
Location Drift				0.102***		0.081**				
				(0.032)		(0.032)				
Industry Drift					-0.137***	-0.135***				
					(0.020)	(0.020)				
Drift Share							-0.074***			
							(0.024)			
Average Drift Score								-0.025*		
								(0.015)		
Drift Share (excl. Stage Up)									-0.105***	
									(0.022)	
Average Drift Score (excl. Stage Up)										-0.061***
										(0.016)
Fund Sequence	0.018***	0.019***	0.019***	0.019***	0.022***	0.024***	0.019***	0.019***	0.021***	0.020***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Fund Sequence squared	0.006***	0.007***	0.006***	0.006**	0.007***	0.006***	0.007***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fund Size	0.026***	0.026***	0.026***	0.024***	0.025***	0.022***	0.027***	0.027***	0.027***	0.027***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Fund Size squared	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Stage Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Region Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Vintage Year Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2,718	2,718	2,718	2,718	2,718	2,718	2,718	2,718	2,718	2,718
Adj. R^2	0.3241	0.3267	0.3282	0.3294	0.3389	0.3476	0.3271	0.3250	0.3319	0.3296

To include the binary drift variables into the fund-level analysis we aggregate the investment level data. This means the respective drift variables in table 2.13 represent the fraction of the portfolio that is classified as the respective drift. Model (2) - (6) in table 2.13 include the four style drift variables first stepwise and finally combined in one regression model. The results of the fund-level performance analysis are very similar to the results of the individual investment success analysis. Model (2) and (3) show that stage drifting has a significant effect on fund performance. *Stage Drift Down* has a negative sign, which can directly be interpreted based on the OLS coefficient. All else equal increasing the fraction of investments representing a downward stage drift by one standard deviation decreases a fund's overall investment success by 1.6 percentage points (specifically, in this case, the exit rate decreases from 49.4% to 47.8%). A comparable effect size with a positive sign can be observed for *Stage Drift Up*. A one standard deviation increase of *Stage Drift Up* increases the exit rate of a fund by 2.1 percentage points.

Unexpectedly, *Location Drift* has a positive effect on a fund's exit rate. The effect of a one standard deviation change corresponds to an increase of the fund performance of 2.0 percentage points. In unreported regressions, we employ a dummy for frequent location drifters and infrequent location drifters, to analyze if the positive effect persists even for funds that undertake only a few cross border investments.[19] The results show, that the positive relationship between fund performance and location drifts is only significant for the frequent drifter group. This indicates that experience in or focus on cross-border investments plays a role in the effect of *Location Drifts*. *Industry Drift* has a negative effect on a fund's exit rate. This confirms that VCs benefit from staying in their specialized industry comfort zone. A one standard deviation increase in *Industry Drift* is associated with a 2.9 percentage points lower exit rate.

The results reported so far might be biased due to the fact, that we do not consider the investment amounts per company in the fund-level drift measures to better account for the real portfolio composition. Further, as before in the individual investment success analysis, we want to rule out that the style drift fractions simply proxy for performance persistence. In unreported regressions, we use the investment amounts as weights for the drift dummies, when we create the fund-level drift variables as an alternative specification and include the exit rate of the VC's last fund as a control for performance persistence. The reported results above are robust to using the investment amount weighted drift variables instead of the equally weighted ones. Including the performance persistence

[19]Funds with a fraction of *Location Drift* of less than 20% are considered infrequent location drifters. However, the results are the same for a 10% or 30% threshold.

control does not change results either, even though we do find evidence for performance persistence, which is perfectly in line with Kaplan and Schoar (2005), who document substantial performance persistence between consecutive funds.

Finally, in models (7) and (8) we analyze the effect of style drifts by combining the different style dimensions into two potential aggregate measures. In model (7) *Drift Share* is the fraction of the portfolio that represents at least one drift. The aggregate effect of style drifting on a fund's exit rate is negative. The coefficient means that a fund without even a single portfolio company that constitutes any style drift, all else being equal, has a 7.4 percentage points higher exit rate than a fund style drifting in every single investment. Model (8) measures aggregate style drift as the *Average Drift Score*, i.e. the number of distinct style drifts divided by the number of portfolio companies. Thus, *Average Drift Score* can take values between 0 and 3 and should even better capture the nuances of aggregate style drift. The negative effect of aggregate style drift on the fund's exit rate holds also based on this measure of aggregate style drift, even though the coefficient is only significant at the 10%-level. The negative effect in models (7) and (8) can be observed, even though we also include upward stage drifts in the measures. When we only consider industry drifts, location drifts, and downward stage drifts, i.e. riskier style drifts as hypothesized in section 2.2.1, for the aggregate measures in models (9) and (10), the coefficient for *Drift Share (excl. Stage Up)* become even more negative and *Average Drift Score (excl. Stage Up)* becomes significant at the 1%-level. The results on aggregate drifts are in line with Bubna et al. (2020). Even though they use a different methodology, that is not fully compatible with our approach of deriving style drifts, Bubna et al. (2020) incorporate the same style dimensions, i.e. industry, location, and stage, into their aggregate drift measure and find the same negative effect of style drifts on performance. This confirms our results and shows that conducting more risky investments decreases a fund's exit rate.

2.5 Conclusion

In this paper, the motivating factors for investment style drifts and their impact on investment performance in the venture capital context are investigated. LPs considering venture capital look for a specific risk-return profile of a venture capital fund that matches their own portfolio choices. Under the assumption that a venture capital fund's implicitly expected investment style is the basis for a LP's capital allocation when GPs deviate from this expected investment style, they might not act in the best interest of LPs.

This paper contributes to the sparse literature on style drifts in venture capital and on potential agency conflicts between LPs and GPs. By examining how economic incentives and venture capital industry conditions influence the probability of style drifts in the three core investment style dimensions (portfolio company development stage, location, and industry) this article distinguishes between style drifts out of necessity and deliberate style drifts. The paper contributes to the literature by connecting all three style drifting dimensions to the underlying risk-taking attitude of VCs at the time of investment. Based on this connection we argue that style drifts represent shifts in the risk profile of a fund. When drifts are deliberate risk-taking decisions motivated by potential compensation benefits for GPs, they constitute an agency conflict.

The findings suggest that in fact, style drifts are likely representing an agency conflict between GPs and LPs. The results lend support to the hypothesis that compensation incentives overweigh employment incentives for well-performing VCs, who therefore increase the risk to benefit from higher compensation potential, when they feel confident, that they will be able to raise a follow-on fund. Results show that well-performing VCs exhibit a higher risk-taking attitude and thus are more likely to perform downward stage drifts and location drifts, but less likely to perform upward stage drifts. Notably, industry drifts do not follow the same pattern. The analysis suggests that industry drifts are mostly driven by necessity. Overall, results suggest that VCs have a higher risk-taking attitude regarding all investment style drifts when public markets are rising. Additionally, there is evidence for the hypothesis that increasing competition for high-quality investments also increases the probability of style drifts, irrespective of the associated risk shift. Lack of deal flow in the preferred investment style is consistently increasing the probability of style drifts across all style dimensions. Further, there is at least some evidence suggesting that competition induced by high fund inflows also increases the probability of style drifts occurring. All reported results are robust to various alternative model specifications.

Looking at the impact of style drifts on overall fund performance, the results show that aggregate style drifts have a negative impact on a fund's exit rate. The effect can be disentangled into the individual style drift dimensions, which then show varying effects. The fraction of a funds portfolio representing downward stage drifts and industry drifts decreases a fund's exit rate, while location drifts and upward stage drifts increase the exit rate. The effect of location drift can be attributed to a small number of frequent-location-drifter funds. Funds with a fraction of location drifts of less than 20% do not show a significant effect on the exit rate. The fund-level results are supported by the findings of the individual investment success analysis, which shows the same general effects even after controlling for performance persistence and the potential endogeneity of exit success and style drifting.

The results overall cannot fully resolve the style drift puzzle. On the one hand, the analysis of the motivational factors for style drifts shows some evidence for both, drifts out of necessity and drifts as deliberate risk-taking decisions. Yet, fund performance is consistently negatively affected by aggregate style drift, implying that LPs do not benefit from style drifts in terms of better performance. Thus, this still leaves the question open, why style is not contractually fixated. The results have further practical importance as they question the optimality of the incentive structure in typical limited partnership agreements for closed-end funds with the connected necessity for frequent fund-raising cycles.

While this paper shows that style drifts in the current fund are related to the balance of compensation and employment incentives, i.e. the confidence of being able to raise a large follow-on fund, it also leaves unanswered some other interesting questions. How do style drifts eventually affect fundraising success? Do LPs consider past style-deviation patterns when GPs try to raise new funds? It could be interesting to find out, whether past style drifting is related to the probability of raising a follow-on fund or the size of the follow-on funds. Our analysis includes a large number of different countries, however, we only touch on the relationship between style drifts and formal and informal institutions. Further research could shed more light on country differences concerning style drifts. How are cultural aspects related to the occurrence of style drifts? Is the negative effect of style drifts on performance worse in countries with a worse legal system? Other interesting issues to analyze are e.g. style drifting in the light of COVID-19 or the entrepreneur's perspective on style-drifting GPs. Has GPs' style-drifting behavior changed in the post-COVID-19 period because of changed risk-taking attitudes? Do GPs get less involved in investments that represent style drifts because of a decreased ability to offer value-adding services? We leave these questions open for further research.

3

Essay 2 – Tell Me Something New: Startup Valuations, Information Asymmetry, and the Mitigating Effect of Informational Updates

Abstract

A high level of information asymmetry is characterizing for venture capital investments making new information about entrepreneurial companies especially valuable for a venture capitalist's valuation process. This paper uses text classification and text mining methodology to extract structured data about capital allocation plans in a unique sample of 1,550 European funding rounds that serves as proxy for the private informational updates shared with investors by entrepreneurs. We show that venture capitalists incorporate the content and specificity of information into their valuation process. Further, results confirm that the value of new information is dependent on the prevailing level of information asymmetry.

Keywords: venture capital, valuation, information asymmetry, text analysis

Bibliographic Information

Lukas Koenig and Julius Tennert (2022). "Tell me something new: startup valuations, information asymmetry, and the mitigating effect of informational updates". In: *Venture Capital* 24.1, pp. 47–69. DOI: 10.1080/13691066.2022.2026744

3.1 Introduction

The main goal of VCs is to allocate their capital to the right entrepreneurial companies at the right valuation, in order to maximize the financial returns of their venture capital funds. But what exactly constitutes 'right' in this context and how can VCs identify these entrepreneurial companies? Assessing entrepreneurial companies is the bread-and-butter business of VCs. However, there is only limited potential to conduct classical financial due diligence for valuation purposes, as the value of an entrepreneurial project typically lies in intangible assets in the first years of new ventures. It is characteristic for entrepreneurial companies to go through different life cycle phases developing and commercializing the project (Lewis and Churchill 1983; Gartner 1985; Bhave 1994) with a diminishing failure risk in each consecutive phase. To explore and develop the project throughout these phases they need substantial capital from VCs acting as outside investors faced with an informational disadvantage (Admati and Pfleiderer 1994; Cornelli and Yosha 2003). The entrepreneur on the other hand usually has an informational advantage regarding the company's future prospects and success probability (Shane and Stuart 2002). Thus, VCs need to learn about the entrepreneurial company's current state and future trajectory through regular informational updates (Bergemann and Hege 1998; Y.-W. Hsu 2010) reducing the risk of overvaluations or adverse selection rooted in informational asymmetries.

This paper has two objectives. First, it seeks to advance the understanding of the relevance of information asymmetry in venture capital funding relationships and second, it explores the mitigating role of informational updates in funding rounds. We analyze the valuation effect of newly arriving information with different content and different levels of specificity under different levels of information asymmetry. Building on prior work in the fields of agency theory the paper emphasizes the general relevance of information asymmetries between entrepreneurs and VCs in funding relationships. We argue that the staging of investments is a key strategy to reduce information asymmetries in venture capital investments allowing VCs to periodically learn about entrepreneurial companies' prospects via informational updates. We lay out the argument that both, information content and information specificity, are considered by VCs in their investment and valuation decisions. Information content signaling that the entrepreneurial company is in a later life cycle phase and more specific information enabling efficient monitoring is predicted to be related to higher valuations. Further, we hypothesize that the relevance of new information depends on the relative level of information asymmetry between VC and entrepreneur in a given funding round, i.e., that new information is less impactful under already low levels of information asymmetry. Thus, this paper contributes to

prior theoretical literature analyzing the relationship between VCs and entrepreneurs with a focus on agency conflicts and information economics (Neher 1999; Wang and Zhou 2004; Hellmann 2006; Shepherd and Zacharakis 2001; Arcot 2014; Sievers et al. 2013) providing empirical evidence for the role of information in venture capital funding relationships that so far has been analyzed theoretically only (Bergemann and Hege 1998; Bergemann et al. 2010; Y.-W. Hsu 2010). To do so, this paper relies on a unique sample of 1,550 European funding rounds containing valuations and textual descriptions of capital allocation plans regarding the raised money. The textual descriptions are used as proxy for the private information shared between entrepreneur and VC during a funding round. We use text classification and text mining methodology to extract structured data about the content and specificity of the informational update for the empirical analysis. The results of our analysis indicate that VCs in fact learn from informational updates during funding rounds and incorporate both the information's content and the information's specificity into their valuation process. More specific information and positive signals are statistically significant related to higher valuations. Furthermore, the results confirm that new information has a higher impact on valuations, when information asymmetry is high.
The remainder of this paper is structured as follows. First, section 3.2 explains the relevance of informational updates in funding relationships under asymmetric information, gives an overview of related literature, and develops testable hypotheses. Next, section 3.3 introduces the sample, details the text analysis methodology, goes over the variable construction for the empirical analysis, and provides descriptive statistics. Section 3.4 covers the econometric methodology and discusses the results and limitations. Eventually, section 3.5 concludes.

3.2 Informational Updates in Venture Capital

3.2.1 Information Signals and Information Asymmetries

Information asymmetries between entrepreneurs and their potential capital providers are a central reason for the existence of specialized VCs. The high uncertainty surrounding an entrepreneurial company's ability to generate future cash flows emphasizes the importance of information about an entrepreneurial project's prospects of success in a funding relationship. The general idea of the importance of asymmetric information and the problem of adverse selection goes back to the seminal work of Akerlof (1970) and the market for 'lemons'. Informational asymmetries in venture capital arise, because it can be assumed that the entrepreneur has more knowledge about the quality and true value of the venture than a potential VC. This form of information asymmetry is broadly referred to as the issue of hidden information in the agency theory literature (Jensen and Meckling 1976). Amit et al. (1998) even argue that VCs' raison d'être is their ability to reduce the cost of informational asymmetries in the funding process of entrepreneurial companies.

In order to mitigate adverse selection problems VCs rely on various mechanisms such as screening, due diligence, and monitoring (Fried and Hisrich 1994; Cumming 2006). Kaplan and Stromberg (2001) emphasize the difficulty of disentangling the different mechanisms. They argue that all mechanisms rely on the collection of information about the entrepreneurial company either before an initial or a potential follow-up investment into the company. Via screening and due diligence VCs try to exploit all information available to them to estimate the true value of the entrepreneurial company, while monitoring activities are supposed to influence entrepreneurs to act in the best interest of the VC (Bernstein et al. 2016) by among others verifying claims they make about the entrepreneurial company. Furthermore, to control investment risk it is common practice for VCs to stage investments (Sahlman 1990; Wang and Zhou 2004). By spreading the total funding into multiple financing rounds, VCs have the discretion to make follow-on investments or abandon an entrepreneurial company, depending on the information the VC learns about the progress of the entrepreneurial company during each financing round (Gompers 1995). It follows that staging is valuable to the VC, because it allows the VC to learn more about the entrepreneurial company over time, which mitigates the agency risks in the funding relationship. With each new piece of information, the VC can adjust the probability of whether the company is of high or low quality and use this for his internal valuation process. Bergemann et al. (2010) model the venture capital investment process and show that VCs learn from newly arriving informational updates and adjust the success probability they use for decision making in the funding relationship. This only works, however, if the entrepreneur does provide information to the VC. Milgrom (1981) and Grossman (1981) show with theoretical considerations in the area of information economics that it is rationale to reveal private information for all entrepreneurs. The basic idea is as follows: A rational VC will suspect that a rationale entrepreneur withholding information only does so, because the company is of average or even inferior quality. Any company owning information proofing its superior quality, would reveal this information. Therefore, all information is revealed, as not revealing any information would send a worse signal than revealing negative information. The theoretical arguments are supported by some empirical evidence as well. Bollazzi et al. (2019) show that entrepreneurs indeed send quality signals to VCs in order to reduce information asymmetries.

Thus, in each funding round, VCs receive informational updates about the progress and quality of the entrepreneurial company. This means that through staging a VC's investment decision can be based on more and higher-quality information compared to the case of only one single upfront investment (Dixit and Pindyck 1994) and subsequently the VC can decide to abandon the investment in every funding round. However most importantly, besides the pure abandonment decision, the VC can also include the content of the informational update about the entrepreneurial company into his valuation. Consequently, the VC is able to adapt the valuation based on the signal he receives in form of an informational update from the entrepreneur. If the entrepreneur's informational update sends a positive signal about the company's progress, its value is higher, if it sends a negative signal about the company's progress, its value is lower.

H1a: Positive information signals are related to higher valuations

H1b: Negative information signals are related to lower valuations

3.2.2 Information Specificity

In addition to the raw content of an informational update its specificity is also an important factor for the VC's valuation for two reasons. First, information sharing comes at a cost for the entrepreneur (Verrecchia 1983; Dedman and Lennox 2009; Ellis et al. 2012; A. Ali et al. 2014). Specifically in the case of venture capital investments, Cox Pahnke et al. (2014) argue that competitive information leakage by investors is an issue for entrepreneurs. They find evidence for their theory that indirect ties (through a shared VC) between competing companies can lead to the leakage of internal information and thus the loss of a competitive or technological advantage of the entrepreneurial company. So as long as entrepreneurs only share general information with the VC they have a low risk of information leakage. However, the more specific information an entrepreneur shares, the higher the risk of information leakage. Thus, entrepreneurs need to be compensated for the risk they get exposed to for sharing highly specific information with VCs, in form of a higher valuation. Second, VCs spent considerable time and effort, both in terms of money and opportunity cost, on monitoring activities (Gompers 1995; Bernstein et al. 2016). This task is considerably easier for the VC the more ex-post verifiable information the VC collects before committing to a funding round. Thus, the disclosure of ex-post verifiable information, makes it more likely that the informational update of the entrepreneur is actually truthful. In fact, Grossman (1981) shows it is only rationale for entrepreneurial companies of high quality to share ex-post verifiable information, if they can back the information up with results after disclosure.[1] Providing ex-post verifiable information to the VC, can thus be interpreted as a signal of company quality for the VC. However, only specific information can be verified unambiguously.[2] Thus, it can be expected that VCs take the specificity of an informational update into account when they asses the valuation of the entrepreneurial company. More specific informational updates should therefore be associated with higher valuations, independent of the information content of the informational update.

H2: Valuations are higher if the informational update contains more specific information

3.2.3 Level of Information Asymmetry

While the generally high level of information asymmetry between entrepreneur and VC compared to e.g., investing in public markets is the foundational argument for the value of informational updates in venture capital, the actual level of information asymmetry is not homogenous in every single entrepreneur-VC funding relationship. So far, the argument laid out in this section was that informational updates are valuable as they reduce the level of information asymmetry between entrepreneur and VC, thus allowing the VC to make better investment decisions. Hence, it is logical to assume that the relative level of information asymmetry within the universe of venture capital investments also influences how VCs incorporate informational updates into their valuation decisions. There are two main opposing arguments to be made here. First, if the entrepreneur has already released much of his private information to VCs, providing additional information does not substantially further decrease the already low level of information asymmetry. For example, Dierkens (1991) uses the same line of argumentation in the context of public market reactions to negative company announcements and shows that the current level of information asymmetry is related to the stock price effect of new equity issue announcements. They show that the stock market reactions are less negative when the level of information asymmetry is already low and thus the new announcement does only reveal minor additional information about the true state of the firm.

This first line of argument, however, does not consider the effect of moral hazard in entrepreneur-VC funding relationships. An entrepreneur can choose to behave opportunistically (Bergemann and Hege 1998; Holmström 1979), e.g., the entrepreneur could

[1] Grossman (1981) argues that general statements about e.g., the quality of a product would always lead a rational buyer of that product to assume the quality to be the minimum that still fits the general statement.

[2] While the information that a company will 'grow sales' is good news, it is very general information. Disclosing more specific details such as 'doubling sales of existing product X' is easily verifiable ex-post.

report false information to ensure continued funding or a higher valuation of the entrepreneurial company for private benefits. Hence, the second argument is as follows. If there is already a low level of information asymmetry between entrepreneur and VC at the time of the release of a new informational update, the VC will have higher confidence that the entrepreneur discloses truthful information. Thus, the VC will actually consider the information received under low information asymmetry more trustworthy than information received under high information asymmetry. This argument is closely linked to the role of trust in venture capital funding relationships. Bottazzi et al. (2016), for example, show that trust plays a significant role in venture capital investments. They find that the probability of making an investment increases with higher levels of trust between entrepreneurs and VCs. In summary, the two arguments result in two possible, opposite hypotheses regarding the moderating role of the level of information asymmetry on the incorporation of informational updates for valuation decisions.

H3a: The valuation effect of information signals is lower under low information asymmetry

H3b: The valuation effect of information signals is higher under low information asymmetry

3.3 Data and Methodology

3.3.1 Sample Construction

As a starting point of our sample construction, we collect data about private equity funding rounds from the Dow Jones Venture Source (formerly VentureOne) database, which has already been widely used in private equity research (e.g., Cochrane 2005; Gompers et al. 2009; Ewens and Rhodes-Kropf 2015). We limit our sample to funding rounds of portfolio companies in 15 European countries.[3] In addition to the geographical focus on Europe, we also limit the timeframe. Because of deficient coverage of European companies before 2004, we only consider companies that have received venture capital funding in the timeframe between the years of 2004 and 2015. The database lists some funding rounds that entail debt financing, corporate rounds or bank affiliated venture financing. We exclude all these observations from our sample, as they do not represent standard venture capital funding rounds. This leaves us with 6,849 unique funding rounds, for which we are able to obtain funding round and company characteristics. However, the database does not provide the full set of information for every single funding round. To

[3]The sample includes companies from the following countries: Belgium, Austria, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, United Kingdom, Denmark, Finland, Sweden

test the hypotheses described in section 3.2, we require both, valuation data and capital allocation plans as proxy for the informational update of the entrepreneurial company, to be available in order to include a funding round into our sample. Unfortunately, the availability of the necessary information is not evenly distributed in the database. To keep the sample balanced in the cross section, we only include the most recent funding round per company. These requirements leave us with a final sample of funding rounds of 1,550 unique companies[4] with the involvement of 1,590 unique investors, for which all variables for the empirical analysis can be constructed. The final step in the sample construction process might potentially introduce a sample selection bias into our analysis (Heckman 1979). We address this concern econometrically in section 3.4. Additionally, we use exchange rates from Thomson Reuters Datastream and inflation data from Eurostat, to convert all monetary values in the database to inflation adjusted Euro amounts with 2004 as the reference year.

3.3.2 Text Analysis Methodology

For each funding round in our sample the database provides a textual description of how the portfolio company plans to allocate the to be raised capital. This information is used as a proxy for the informational update that a portfolio company discloses to VCs in a funding round. The length of these non-standardized text segments ranges from 7 to 118 words or 38 to 741 characters, respectively. We rely on text analysis and text mining techniques to extract structured data about the informational updates' content and specificity for our empirical analysis.

First, we build on work in the field of text classification for the evaluation of the content of the informational updates. More specifically, we rely on the general idea of sentiment analysis (Pang and Lee 2008; Chenlo and Losada 2014; Alessia et al. 2015) that has already been widely used in finance research, e.g., in the context of stock markets (e.g., Tetlock 2007; Baker and Wurgler 2007; Renault 2017), central bank policy (e.g., Gulen and Ion 2016; Hansen and McMahon 2016), or venture capital (e.g., Tumasjan et al. 2021). We adopt the concept of sentiment analysis for this paper by introducing a polarity scoring model, that extracts and quantifies the polarity of the information content of an informational update. We exploit the textual descriptions of the capital allocation plans to compute a polarity score based on three information signal categories that are defined by a startup's life cycle phases (Lewis and Churchill 1983; Gartner 1985; Bhave 1994). Generally, the life cycle consists of (1) the incubation of an entrepreneurial idea, (2) the

[4]Around 35%, 20%, and 12% of the sample companies are from the United Kingdom, from France, and from Germany, respectively, while the other countries in the sample have roughly equal shares.

acceleration of the entrepreneurial project, and the setup of the company, and (3) the overall growth and take-off of the business in this order.

From a VC's point of view, the value of a portfolio company is driven by its ability to generate cash flows (Dittmann et al. 2004; Pintado et al. 2007; Laitinen 2019). That is why each of the three life cycle phases can be assigned with a different polarity signal value, depending on how fast and how certain the investor can expect his investment to generate cash flows. In order to create our proxy for the information content of an informational update via its polarity, we assign each phase a numerical signal value. We define the acceleration phase as the reference polarity signal with a signal value of 0. Consequently, activities connected to the incubation phase then correspond to negative information (signal value -1), as they signal that the startup is conducting activities that are further away from generating cash flows. Vice versa, activities connected to the growth phase then correspond to positive information (signal value $+1$), as they signal that the startup is using the funds for activities that have a higher probability of resulting in earlier cash flow generation.

To operationalize this signal approach, we rely on the structure of the capital allocation plans provided by the database. The capital allocation plans the database provides for each funding round about the entrepreneurial companies contains information in the three areas of (I) research and development, (II) marketing and sales, and (III) overall professionalization of business operations. Thus, we use these areas to classify each text based on activities in these three areas to compute the overall polarity score. Panel A in table 3.1 illustrates the polarity scoring model described above and provides examples for the activities within the three information areas for each life cycle phase. For each capital allocation plan in the sample at least two persons independently identify all activities in the three areas mentioned above and manually assign them their individual signal value according to Panel A. In case of deviating assessments a third person resolves the disagreement. This is done to ensure consistency in the application of the scoring model across all capital allocation plans in the sample. As some texts contain several activities, *polarity* is defined as the sum of all identified individual signals contained in the text. Panel B in table 3.1 shows three examples for our polarity scoring methodology. For instance, in column three there are two polarity signals in the informational update. The first one (expansion of sales activities) is activity in the area of marketing and sales that points to the acceleration phase. The second one (international expansion) indicates the growth phase. In sum, the informational content of this capital allocation plan is scored with a *polarity* of $+1$, i.e., a positive signal.

Table 3.1.: Text Analysis Methodology Overview: Polarity and Specificity Approach

This table illustrates the text analysis methodology. Panel A depicts the polarity score model. The rows correspond to the phases of the startup life cycle, the columns represent the three areas for which the sample provides information. Examples for typical activities in a specific life cycle phase within the information areas are given. Panel B shows three exemplary analyses of both polarity scoring and specificity computation.

Panel A: Polarity score model

	Signal Value	(I) Research and Development (RD)	(II) Marketing and Sales (MS)	(III) Business Operations (BO)
(1) Incubation	-1	Development of a new product	First marketing and sales activity	
(2) Acceleration	0	Commercialization of a product	Expansion of existing sales activities	Recruiting and increase of headcount
(3) Growth	1	Differentiation of product portfolio	International expansion	Increase of production capacities, Formation of alliances, M&A activity

Panel B: Exemplary application of polarity scoring and tf-idf in the sample

Text	The funding will be used to help kick-start sales of the company's product.	The funding will be used to build the first phase of a next-generation data center in Liverpool, create cloud computing facilities, and for the improvement of infrastructure.	The company intends to use the funding to expand to Belgium, in a two-step approach. It will initially focus on an online store, and follow up with an off-line cafe location and design store in Antwerp.
Pre-processed Text	help kickstart sales product	build first phase nextgeneration data center liverpool create cloud computing facilities improvement infrastructure	expand belgium twostep approach initially focus online store follow offline cafe location design store antwerp
Individual Signals	MS - Incubation (-1)	BO - Growth (+1)	MS - Acceleration (0) and Growth (+1)
Polarity Score	-1 (negative signal)	1 (positive signal)	1 (positive signal)
Tf-idf per term	'help': 4.4, 'sales': 3.7, 'product': 2.9, ...	improvement': 6.8,' 'facilities': 6.8, 'computing': 6.8, ...	store: 13.7, online: 6.8, focus: 6.8, ...
Specificity	12% (low)	42% (high)	64% (high)

Second, in order to measure the *specificity* of the content of the informational update we draw on term frequency–inverse document frequency methodology (tf–idf). Tf–idf is a numerical bag of words text mining method that quantifies the importance of specific terms in a text document within a larger document corpus[5] relative to other terms in the corpus (Ramos 2003; Qaiser and R. Ali 2018). The tf-idf concept is well established in the information theory literature, because the concept not only allows to retrieve the most important information from text documents but also allows to quantify the amount of information a text contains in order to use it in empirical models (Wong and Yao 1992; Aizawa 2003). The basic idea of tf–idf is to combine term frequency (tf), i.e., the notion that words that appear frequently in one document have high importance for the content this document, and inverse document frequency (idf), i.e., the notion that words that appear in only few documents are characteristic for these documents. More precisely, tf–idf is computed as follows

$$\text{tf-idf}(t, D) = \text{tf}(t, D) \cdot \text{idf}(t), \tag{3.4}$$

where $\text{tf}(t, D)$ is the frequency of term t in document D and $\text{idf}(t)$ is the logarithm of the total number of documents in the corpus of documents divided by the number of documents containing term t at least once. It follows that tf-idf is highest for terms that occur frequently in one document, but not in any other document.

For the application in this paper, we exploit this characteristic of tf-idf to identify relatively more or less specific informational updates within the corpus of all capital allocation plans. The rationale is as follows: Texts that only contain general language about capital allocation plans consist of terms that occur in many other capital allocation plans, as well, while a more specific capital allocation plan also contains terms that ideally do only occur in this very statement. Terms that occur in many statements are more general and consequently get assigned lower tf-idf values. Thus, the textual description of more specific capital allocation plans will result in higher average tf-idf values based on equation 3.4. Therefore, tf-idf can be interpreted as specificity proxy within the corpus of capital allocations plans for the application in this paper. To create the information specificity proxy, we first apply standard text cleaning and stop word[6] removal procedures, before we compute the average tf-idf value for each document in the corpus. For easier interpretation and because the absolute tf-idf values have no special

[5] In text mining applications a corpus is a collection of individual text documents containing natural language. In this paper the corpus consists of the individual textual descriptions of the planned capital allocation of startups.

[6] We use the standard English stop word lexicon provided by the *nltk* python package (Bird et al. 2009) and add further custom context specific stop words.

meaning in our context, we define *specificity* as the average tf-idf of all terms of a funding round's informational update normalized to unity. As a result of the procedure, it is then possible to rank the capital allocation plans relatively from the most specific to the least specific one. For the empirical analysis, we use the median *specificity* to split the sample into observations with relatively low and high information specificity to account for the fact that tf-idf is only a coarse measure for our purpose. Panel B in table 3.1 stylizes the tf-idf approach for three exemplary capital allocation plans. The texts in columns two and three have high information specificity, while the text in column one has low information specificity relative to all other texts in the corpus based on the median *specificity* as the distinguishing feature.

3.3.3 Variables Construction

Table 3.2 summarizes the variables for the empirical analysis and provides an overview of the variables' definitions.

The main dependent variable for the empirical analysis, *valuation*, is the post-money valuation at the time of the funding round in million Euro.[7] It is the value of the company after investors incorporated the informational update into their valuation consideration. Furthermore, there are three central independent variables. First, *polarity* captures the information content of the informational update, i.e., the extent of how positive or negative the information content is. Its construction is described in detail in section 3.3.2. From *polarity* we additionally derive two dummy variables. *Positive signal* is equal to one for *polarity* > 0, and zero otherwise. Following the same logic, *negative signal* is equal to one for *polarity* < 0, and zero otherwise. We introduce these additional dummies, to allow positive and negative information signals to have asymmetric effect sizes on valuations in the regression analysis. Second, *specificity* is proxying for the degree of specificity of the informational update, as described in 3.3.2. We use the sample's median *specificity* to create another dummy variable for *high specificity*. It is equal to one for all observations where *specificity* $>$ median and zero otherwise. And third, we create a proxy for the level of information asymmetry at the time of the funding round. We exploit the funding round's investor syndicate composition[8] to categorize funding rounds into rounds with a high or low level of information asymmetry between VCs and entrepreneurs. Follow-on investors have access to more private information of the entrepreneurial firm (Admati and Pfleiderer 1994), thus information asymmetries are much lower if a prior investor is part of the syndicate. We consider the level of

[7] For the regressions in section 3.4 the variable is log-transformed.

[8] This also includes investments with only one single investor, which, strictly speaking, is not a syndicate.

Table 3.2.: Overview and Definition of Main Variables of Interest

This table provides an overview and the definition of all variables used in the regression analyses.

Variable Name	Unit	Definition
Dependent Variable		
Valuation	ln(mn. Euro)	The natural logarithm of the company's post-money valuation in inflation adjusted million Euro at the time of the funding round.
Independent Variables		
Polarity	#	The sum of all identified individual information signals in the capital allocation plans, i.e., the extent of how positive or negative the information content is; an individual numerical signal value (−1, 0 or +1) is assigned to each startup lifecycle phase (incubation, acceleration, growth) based on how fast and how certain the investor can expect his investment to generate cash flows.
Positive Signal	dummy	Dummy that is equal to one for *polarity* >0, and zero otherwise.
Negative Signal	dummy	Dummy that is equal to one for *polarity* <0, and zero otherwise.
Specificity	%	The average term frequency-inverse document frequency (tf-idf) of all terms in the funding round's capital allocation plan normalized to unity.
High Specificity	dummy	Dummy equal to one for *specificity* > median(*specificity*), and zero otherwise.
Low Asymmetry	dummy	Dummy variable equal to one for funding rounds with syndicates comprising at least one prior investor of the company, and zero otherwise.
Controls		
No. of Investors	#	The number of VCs participating in the funding round.
Company Age	ln(years)	The natural logarithm of the age of the company in years at the time of investment.

information asymmetry of funding rounds in which none of the investors has already invested into an earlier funding round of the same company as high, while we consider the level of information asymmetry as low, if any of the investors has already formed a relationship with the company in an earlier funding round. Thus, *low asymmetry* is a dummy variable equal to one for low levels of information asymmetry between VCs and entrepreneurs and zero otherwise. The rationale of this proxy is based on the argument that existing investors have had time to gain more detailed insights into the company's performance, the execution quality of the entrepreneurial project, the entrepreneurial team, etc., which lowers the level of information asymmetry for the whole syndicate. Bygrave (1987) shows that it is a reasonable assumption that 'insider' VCs share their information in the syndicate, because VCs form syndicates mainly for the very purpose of information sharing. In order make sure that the proxy does not capture too much noise from miss-classifications due to incomplete funding histories, we exclude all funding rounds of companies from the sample for which it cannot be clearly determined if the full funding history is available in the database, whenever we use the proxy in the empirical analyses.

3.3.4 Sample Overview and Descriptive Statistics

Panel A in table 3.3 describes the full sample and provides descriptive statistics for the main variables. The median investment year is 2013, the average *valuation* is about 16 million Euro and the average company is 5.2 years old at the time of the funding round. There are on average 2.6 investors participating in a funding round and 68% of all funding rounds are syndicated. *Polarity* is slightly positive (0.13) on average and the mean *specificity* (normalized to unity) is 33%.

The three additional panels split the sample into subsamples along the three central independent variables of this paper. Panel B separates the sample according to the polarity score. It gives first indicative evidence for **H1a** and **H1b**, that state that information polarity and company valuation are related. The average valuation is higher in funding rounds with positive information signals (21.0 million Euro) compared to the valuation of companies in funding rounds with negative information signals (9.8 million Euro). The difference in means is highly statistically significant in unreported t-tests. Panel C splits the sample according to the level of information specificity of the informational update and shows that company and round characteristics besides *specificity* are similar for both subsamples. Again, the biggest and statistically significant difference between the two subsamples can be observed for the mean *valuation* (18.2 vs. 13.7 million Euro), which lends support to **H2** concerning the relationship of valuations

Table 3.3.: Sample Overview and Descriptive Statistics

This table provides an overview of the sample of 1,550 unique funding rounds. Each observation represents a funding round in which one or several a venture capital firms invest into an entrepreneurial company. The table shows median values for the year of investment. Means are shown for all other variables. For the full sample the standard deviation is presented in parentheses. *Valuation* is the valuation of the entrepreneurial company in million Euro. *Age* is the age of the portfolio company in years at the time of the funding round. *No. of Investors* is the number of VCs participating in the funding round. *Syndicated?* is the share of syndicated funding rounds. *Polarity* is the polarity score of the funding round's informational update. *Specificity* is the average tf-idf of the funding round's informational update normalized to unity. Panel A shows the full sample. Panel B separates the sample according to the polarity score. Panel C splits the sample according to the level of information specificity of the informational update. Panel D categorizes the sample according to the level of information asymmetry in the funding round. Panel D excludes all funding rounds of companies for which the database does not have the full funding history available.

	N	Year of Investment	Valuation	Age	No. of Investors	Syndicated?	Polarity	Specificity
Panel A: Full Sample								
All Obs.	1,550	2013	16.0	5.2	2.6	68%	0.13	33%
		(2)	(46.7)	(3.9)	(1.6)	(47%)	(0.92)	(11%)
Panel B: Information Content (Polarity)								
Negative	401	2013	9.8	4.0	2.6	71%	-1.13	33%
Neutral	562	2013	15.1	5.2	2.7	69%	0.00	34%
Positive	587	2013	21.0	5.9	2.5	65%	1.10	32%
Panel C: Information Specificity								
High	774	2013	18.2	5.4	2.8	71%	0.08	41%
Low	776	2013	13.7	5.0	2.5	66%	0.18	25%
Panel D: Level of Information Asymmetry								
High	334	2013	17.4	5.4	2.2	63%	0.13	31%
Low	552	2014	25.4	6.4	3.6	90%	0.29	34%

and information specificity. Finally, Panel D categorizes the sample according to the degree of information asymmetry in the funding round between VCs and entrepreneurs. The companies in the low asymmetry subsample are older (6.4 vs. 5.4 years), have more investors (3.6 vs. 2.2), higher valuations (25.4 vs.17.4 million Euro), and a higher share of the funding rounds are syndicated (90% vs. 63%).

3.4 Empirical Analysis and Discussion

3.4.1 Main Econometric Approach

To test the hypotheses in section 3.2 we are interested in how valuations of entrepreneurial companies and informational updates disclosed in the respective funding rounds are related. We rely on the cross section of valuations in our sample.[9] Hence, we employ pooled ordinary least square models with the natural logarithm of post-money valuations as dependent variable for all regressions. The general specification for all regressions in tables 3.4, 3.5, and 3.6 is:

$$\begin{aligned} Valuation_i = \alpha + \beta Info\ Update_i + \gamma_1 No.\ of\ Investors_i + \gamma_2 Company\ Age_i \\ + \gamma_3 IMR_i + Country\ FE + Year\ FE + Industry\ FE + Stage\ FE + u_i \end{aligned} \tag{3.5}$$

where $Valuation_i$ is the natural logarithm of the valuation of a entrepreneurial company in funding round i and $Info\ Update_i$ is a vector of the independent variables of interest regarding the hypotheses in section 3.2, that depends on the exact specification of each regression. The vector can include *polarity*, *positive signal*, *negative signal*, *high specificity*, *low asymmetry*, and matching interaction terms. According to a systematic overview of startup valuation determinants of Köhn (2018), among the most important factors we need to control for are startup characteristics such as industry, age, and location, funding round characteristics such as investment stage or the number of investors participating in the round, and environmental factors such as cultural factors or market environment. Therefore, we include various fixed effects to rule out an omitted variable bias and other controls for funding round and company characteristics. $No.\ of\ Investors_i$ is the number of VCs participating in funding round i. As higher valuations are typically associated with larger syndicates (Cumming and Dai 2013), we control for this effect. $Company\ Age_i$ is the natural logarithm of the company's age at the time of funding round i. It acts as control for company characteristics, as older firms are associated with higher valuations (Gompers et al. 2006). In addition, *country fixed effects* control for geographic differences in valuations due to institutional and cultural factors, *year fixed effects* control for time varying differences in valuations and different market environments, and *industry fixed effects* control for heterogeneity of valuations across seven major

[9] An alternative approach would be to look at the relative increase of valuations of the same company between two consecutive funding rounds to further control for company characteristics. However, this would have significantly reduced our already small sample size.

industries[10]. Furthermore, company *stage fixed effects* are included to rule out the possibility, that we simply measure the valuation differences between e.g., seed stage and later stage companies. u_i is the estimation error. Finally, IMR_i is the inverse mills ratio from the first stage of a Heckman correction procedure. As noted in section 3.3 our sample might suffer from selection bias. Because of data availability constraints regarding the main variables of interest our sample is most likely a non-randomly selected sample. For example, information about capital allocation plans might only be available from entrepreneurial companies that have positive news to share in order to impress investors or valuation data might only be available for later stage startups that already have a public track record. Hence, all regression models might be affected by a sample selection bias. In order to address this issue econometrically, we rely on a two-stage Heckman procedure (Heckman 1976; Heckman 1979) that allows us to correct for sample selection bias. This is a common approach in the venture capital literature (e.g., Gompers and Lerner 2000a; Nahata 2008), where truncated samples are a frequent issue. To do so, in the first stage of each regressions we use a probit model to estimate the probability of an observation actually being part of the main sample and compute the inverse mills ratio type correction term to be included in the second stage regression as noted above.[11] For brevity, we only report the second-stage ordinary least square regression coefficients with robust standard errors in tables 3.4, 3.5, and 3.6 and omit the first-stage probit results of the selection equation.

3.4.2 Empirical Results

Information Content

Table 3.4 presents basic results connected to **H1a** and **H1b** regarding the information content of informational updates. The coefficients for the included controls are as expected. Valuations in funding rounds with a larger syndicates and older entrepreneurial companies are higher. Concerning both **H1a** and **H1b**, the results broadly confirm the predictions. *Polarity* is highly significant and has a positive sign in models (1) and (2). This means, that valuations are higher for companies that send positive signals, while they are lower for companies that send negative signals. More precisely, a one unit increase in polarity

[10] We use the granular industries provided by the database and cluster them into seven broad industry groups: Consumer Goods, Consumer Services, Energy, Financial and Professional Services, Health, Industrial Goods, and Information Technology.

[11] We include a dummy equal to one for syndicated deals, a dummy equal to one for companies who conducted an IPO, and country, year, industry, and stage fixed effects in the first stage selection model of the two-stage Heckman procedure.

Table 3.4.: Basic Regressions Analyzing Information Content

This table reports the results of pooled OLS regressions studying how valuations are related to the content of informational updates. Only the second stage of a two-stage Heckman procedure correcting for sample selection bias is reported. The dependent variable *Valuation* is defined as the natural logarithm of the company's valuation in the respective funding round. The sample is at the funding-round level. *Polarity* is the polarity score of the funding round's informational update. *Positive Signal* is a dummy that is equal to one for *Polarity* > 0, and zero otherwise. *Negative Signal* is a dummy that is equal to one for *Polarity* < 0, and zero otherwise. *No. of Investors* is the number of VCs participating in the funding round. *Company Age* is the natural logarithm of the age of the company at the time of investment. All regressions are estimated with a constant term and include the inverse mills ratio from the first-stage Heckman procedure (both not reported). Robust standard errors are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Polarity	0.126***	0.089***						
	(0.025)	(0.024)						
Positive Signal					0.188***	0.146***	0.138**	0.122**
					(0.049)	(0.047)	(0.055)	(0.053)
Negative Signal			-0.197***	-0.121**			-0.133**	-0.065
			(0.056)	(0.052)			(0.063)	(0.058)
No. of Investors	0.080***	0.110***	0.079***	0.109***	0.081***	0.111***	0.080***	0.110***
	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Company Age	0.342***	0.188***	0.351***	0.194***	0.351***	0.191***	0.344***	0.189***
	(0.042)	(0.039)	(0.042)	(0.039)	(0.042)	(0.039)	(0.042)	(0.039)
Country FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Stage FE	no	yes	no	yes	no	yes	no	yes
Adj. R^2	0.391	0.444	0.387	0.442	0.387	0.443	0.389	0.443
Observations	1,550	1,550	1,550	1,550	1,550	1,550	1,550	1,550

in model (2) corresponds to a roughly 9% higher valuation.[12] Besides our main variable for information content, *polarity*, we also include the two dummies *positive signal* and *negative signal* in the analysis, to allow asymmetric effect sizes for positive and negative information signals. In each model specification all coefficients have the predicted signs. The effect of *positive signal* is about one third larger in magnitude than the effect of *negative signal*. The significance for *negative signal* decreases, when we include both dummies in the regression in models (7) and (8), however, the two dummies are highly correlated by construction. Thus, we are not concerned by this observation, regarding the overall results.

[12] As the dependent variable is log transformed the percentage increase is calculated as follows: $e^{0.088} - 1 = 0.089 \approx 9\%$.

Furthermore, to address any concern, that in fact our proxy for information signals, *polarity*, is simply proxying for a company's investment stage, we estimate all specifications with and and without stage fixed effects. A direct comparison of the specifications with and without stage fixed effects shows consistently larger coefficients for the regression models without stage fixed effects. This confirms that the effect size we are interested in is overestimated, when not controlling for investment stage. However, the smaller coefficients for the polarity variables remain significant, when we include stage fixed effects.

Information Specificity

Table 3.5 reports the results of the analysis of the effect of more specific informational updates. *High specificity* has a positive sign and is statistically significant in models (1) to (3) that do not include any interaction terms between information content and information specificity in the models' specifications. As predicted by **H2**, less general, more specific informational updates are related to higher valuations. Strictly speaking, this means that the group of funding rounds with highly specific informational updates on average has about 11% higher valuations than the less specific group with *specificity* below the median value.
Including the *high specificity* dummy in the model specification, does not alter the sign or magnitude of the coefficients related to information content. This confirms that in fact the two proxies measure different aspects of the informational update. Providing more specific information does have a value independent from the information's content. To test whether the two concepts are completely independent of each other, we further introduce interaction effects in models (4) to (6). From a theoretical point of view it would make sense to assume that the effect size of *polarity* also depends on how specific the information signal contained in the informational update is. In model (5), however, we do not find such an interaction effect. The interaction coefficient is not statistically significant different from zero. But we do find significant interaction terms in model (4) and (6). *Negative signal* $\times$ *high specificity* has a positive coefficient that in absolute terms is about the size of the negative main effect of *negative signal*. This means, that providing highly specific information can offset the negative valuation impact of negative information signals. Even though, the main effect of *high specificity* loses its statistical significance in model (6), the effect size of the interaction term is about twice as large (0.192 vs. ~ 0.110) as *high specificity*'s main effect size in models (1) to (3). Hence, it does pay off for the entrepreneur to share specific and therefore ex-post verifiable information with investors, especially if the actual information signal is negative. Nevertheless, due

to the lack of significance of the main effect we do take this finding with a grain of salt and treat it as indicative evidence only.

Level of Information Asymmetry

Next, we want to shed light on the moderating role of different levels of information asymmetry within the universe of venture capital investments on information content. The results of the analysis are reported in table 3.6. As first step, we include just the dummy variable *low asymmetry* to capture the valuation effect of relatively lower levels of information asymmetry between VCs and entrepreneurs in models (1) to (3). In models (4) to (6) we additionally include an interaction term, to analyze the moderating role of information asymmetry, which is our main concern.

For all models the main effect of *low asymmetry* is highly statistically significant with a positive sign. This means that even after controlling for investment stage and *company age*, companies in funding rounds under lower levels of information asymmetry have on average about 30% higher valuations than their counterparts under high levels of information asymmetry. This shows that it is in the best interest of entrepreneurs to actively reduce information asymmetries. These results are in line with expectations but do not directly address the two alternative hypotheses laid out in section 3.2 regarding the moderating role of *low asymmetry*. **H3a** states that the effect of information signals is lower when information asymmetry is low, while **H3b** states the opposite. Thus, opposite signs for the main effect of information content and the interaction effect with *low asymmetry* would speak for **H3a**, while same signs would support **H3b**. In fact, we do only find consistent evidence for **H3a** in models (4) to (6), supporting the hypothesis that informational updates are of less value when there is already low information asymmetry at the time the information is shared. In each model, the interaction coefficient is of similar magnitude as the main effect, but with opposite sign. In model (4) for example, the coefficient for polarity is 0.148, while the interaction effect's coefficient is -0.125. This means that the resulting valuation effect of *polarity* in funding rounds under *low asymmetry* is significantly smaller ($0.148 - 0.125 = 0.023$). The same moderating effect can be found in models (5) and (6) for both, *positive signal* and *negative signal*. The interaction effect's p-value in model (5) is only 0.11, but the sign and magnitude still match the alternative specifications. Overall, the results strongly support **H3a**.

Table 3.5.: Regressions Analyzing Role of Information Specificity

This table reports the results of pooled OLS regressions studying how valuations are related to the specificity of informational updates. Only the second stage of a two-stage Heckman procedure correcting for sample selection bias is reported. The dependent variable *Valuation* is defined as the natural logarithm of the company's valuation in the respective funding round. The sample is at the funding-round level. *Polarity* is the polarity score of the funding round's informational update. *Positive Signal* is a dummy that is equal to one for *Polarity* > 0, and zero otherwise. *Negative Signal* is a dummy that is equal to one for *Polarity* < 0, and zero otherwise. *High Specificity* is a dummy equal to one if *Specificity* $>$ the median value, and zero otherwise. *No. of Investors* is the number of VCs participating in the funding round. *Company Age* is the natural logarithm of the age of the company at the time of investment. All regressions are estimated with a constant term and include the inverse mills ratio from the first-stage Heckman procedure (both not reported). Robust standard errors are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Polarity	0.086***			0.132***		
	(0.024)			(0.033)		
Positive Signal		0.144***			0.217***	
		(0.047)			(0.066)	
Negative Signal			-0.114**			-0.205***
			(0.052)			(0.069)
High Specificity	0.110**	0.115**	0.112**	0.121***	0.171***	0.063
	(0.045)	(0.045)	(0.046)	(0.046)	(0.058)	(0.054)
Polarity × High Specificity				-0.092**		
				(0.046)		
Positive Signal × High Specificity					-0.149	
					(0.094)	
Negative Signal × High Specificity						0.192*
						(0.100)
No. of Investors	0.108***	0.109***	0.107***	0.107***	0.108***	0.107***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Company Age	0.186***	0.189***	0.192***	0.185***	0.188***	0.192***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Country Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Industry Fixed Effects	yes	yes	yes	yes	yes	yes
Stage Fixed Effects	yes	yes	yes	yes	yes	yes
Adj. R^2	0.446	0.445	0.443	0.447	0.446	0.444
Observations	1,550	1,550	1,550	1,550	1,550	1,550

Table 3.6.: Regressions Analyzing Moderating Effect of the Level of Information Asymmetry

This table reports the results of pooled OLS regressions studying the moderating effect of the level of information asymmetry in the context of informational updates. The sample contains only observations for which a full investment history is available in order to unambiguously identify the level of information asymmetry. Only the second stage of a two-stage Heckman procedure correcting for sample selection bias is reported. The dependent variable *Valuation* is defined as the natural logarithm of the company's valuation in the respective funding round. The sample is at the funding-round level. *Polarity* is the polarity score of the funding round's informational update. *Positive Signal* is a dummy that is equal to one for *Polarity* > 0, and zero otherwise. *Negative Signal* is a dummy that is equal to one for *Polarity* < 0, and zero otherwise. *Low Asymmetry* is a dummy variable equal to one for low levels of information asymmetry and zero otherwise. *No. of Investors* is the number of VCs participating in the funding round. *Company Age* is the natural logarithm of the age of the company at the time of investment. All regressions are estimated with a constant term and include the inverse mills ratio from the first-stage Heckman procedure (both not reported). Robust standard errors are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Polarity	0.076**			0.148***		
	(0.033)			(0.046)		
Positive Signal		0.110*			0.203**	
		(0.062)			(0.102)	
Negative Signal			-0.117*			-0.247**
			(0.068)			(0.099)
Low Asymmetry	0.255***	0.262***	0.256***	0.280***	0.319***	0.206**
	(0.073)	(0.072)	(0.073)	(0.072)	(0.082)	(0.081)
Polarity × Low Asymmetry				-0.125*		
				(0.064)		
Positive Signal × Low Asymmetry					-0.146	
					(0.126)	
Negative Signal × Low Asymmetry						0.237*
						(0.136)
No. of Investors	0.104***	0.104***	0.102***	0.104***	0.104***	0.102***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Company Age	0.314***	0.317***	0.321***	0.314***	0.315***	0.322***
	(0.058)	(0.058)	(0.057)	(0.057)	(0.057)	(0.057)
Country Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Industry Fixed Effects	yes	yes	yes	yes	yes	yes
Stage Fixed Effects	yes	yes	yes	yes	yes	yes
Adj. R^2	0.417	0.416	0.416	0.419	0.416	0.417
Observations	886	886	886	886	886	886

3.4.3 Robustness of Results and Limitations

To strengthen our main results, we conduct two additional robustness checks in unreported regressions. First, we use an alternative proxy for information specificity for the regressions in table 3.5. The alternative proxy relies on the text length of the capital allocation plans. Similarly to the tf-idf approach in the main analysis, we use the median length of all capital allocation plans to distinguish texts with high and low specificity. The alternative proxy does not alter the general results of the main analysis. We find the same overall effects both in magnitude and significance. Second, we conduct the analysis of *low asymmetry* in table 3.6 with an alternative methodology. Instead of relying on interaction terms, we split the sample in the sub-groups of observations under high and low information asymmetry and run separate regressions for both sub-groups. The main difference is, that in this setup all other coefficients, such as the ones for fixed effects, can differ between groups as well. The results are very similar to what we obtain in the main analysis, i.e., the high asymmetry group shows a much higher effect for information content.

While the robustness checks show that our results are robust to an alternative methodology and an alternative proxy, the results of this paper are not without limitations. Firstly, the nature of venture capital funding relationships makes the information shared with investors by the entrepreneur inherently private. Due to the lack of access to this private information, we rely on capital allocation plans provided by Dow Jones Venture Source to proxy for the private information. This might distort our results, as we cannot ensure that the capital allocation plans provided are in fact based on the private information of entrepreneurs and VCs. While most information in the database is collected directly from entrepreneurs, VCs, or limited partners of VCs, we cannot rule out that some capital allocation plans are collected from public sources. Secondly, our sample is too limited to exploit the theoretical longitudinal structure of the data. Ideally, we would not rely on cross-sectional regressions, but rather on the relative valuation effect between two consecutive funding rounds of the same entrepreneurial company. This would allow us to additionally include company fixed effects to better control for all unobserved company characteristics that might influence valuations. However, in many instances the database does not provide capital allocation plans for every single funding round of a specific company, making such an analysis unfeasible. And thirdly, we cannot observe the counterfactual, i.e., cases in which informational updates result in the abandonment of or non-investment in an entrepreneurial company basically representing valuations of zero. Thus, we are only able to measure the effect of informational update within the group of entrepreneurial companies that received (continued) funding in the first place.

The most likely consequence of this distortion is, that the effect of negative information signals is underestimated in our analysis.

3.5 Conclusion

It is a truism that we live in the information age but knowledge about the impact of information and the exact mechanisms of how information is factored into decisions is still scarce. Venture capital funding relationships are characterized by their inherently high level of information asymmetry between VCs and entrepreneurs making information especially valuable in this context. This paper advances the understanding of information asymmetry in venture capital valuation decisions and investigates the role and relevance of informational updates in VC-entrepreneur funding relationships. The paper's main contribution and focus is on the empirical identification of the effect of informational updates on valuations. We use a sample of 1,550 European venture capital funding rounds containing data about the capital allocation plans of the entrepreneurial companies to proxy for the private information that is shared by the entrepreneur during a funding round. Using text classification and text mining algorithms to extract structured data from the capital allocation plans we are able to empirically show that VCs in fact use the periodic informational updates in funding rounds to learn about entrepreneurial companies and incorporate both the information's content and the information's level of specificity into the valuation decision. In this sense, staging can be considered a key strategy to mitigate information asymmetry for VCs. Positive information signals and more specific information are both related to higher valuations.

There are two key contributions of this paper. First, we find evidence that the valuation impact of negative information signals can be offset by the entrepreneur by providing highly specific information. Thus, in practice negative information signals do no automatically lead to lower valuations as long as they are conveyed in a very detailed manner, so they can act as proof point for monitoring activities of VCs. Second, there is clear empirical evidence, that the value of an informational update depends on the current level of information asymmetry between investor syndicate and entrepreneur. Both positive and negative information signals have a higher valuation effect, when no prior investor is part of the investment syndicate and thus information asymmetry is high. Overall, results show, that different levels of information asymmetry exist in venture capital and that they matter both for entrepreneurs and VCs. In practice this means entrepreneurs do only have to spend considerable effort on reducing information asymmetries in funding rounds, when they are faced with a completely unfamiliar syndicate.

While this paper provides evidence for the effect of informational updates in a cross-sectional analysis, it leaves open questions surrounding moral hazard that can be best analyzed in a longitudinal setup. What happens if an entrepreneur behaves opportunistically for private benefits of higher valuations and provides misleading information to VCs? Does opportunistic behavior negatively affect the value of future informational updates, or will investors even abandon the entrepreneurial company when they find out? Answering these questions would further advance the understanding of the role of information in venture capital funding relationships. We will leave these questions open for further research.

4

Essay 3 – Cut from the same Cloth: The Role of University Affiliations in Venture Capital Investments

Abstract

University affiliations of founders and investors in venture capital deals might affect the initial investment decision and the subsequent funding relationship through two channels. First, attending a top university might act as a founder-quality signal to investors, and second, belonging to the same university alumni network might reduce issues related to information asymmetry between investors and founders. This paper exploits a unique sample of 42,101 investments by U.S. and European venture capital firms involving 38,452 individuals to explore the role of university affiliations with a special focus on educational ties between founders and investors. Results confirm that educational ties increase investment likelihood irrespective of a university's quality. Further, the analysis shows that educational ties deepen the funding relationship and increase the willingness of investors to take on riskier investments. Investors are more likely to lead the investment syndicate, take a board seat, or invest in the first round in the presence of educational ties. Finally, the results indicate that an IPO is more likely for investments with educational ties.

Keywords: venture capital, educational tie, university affiliation, matching, funding relationship

Bibliographic Information

Lukas Koenig (2022). "Cut from the same Cloth: The Role of University Affiliations in Venture Capital Investments". Working Paper available at SSRN. DOI: 10.2139/ssrn.4248420

4.1 Introduction

Obtaining venture capital funding is often the only way for entrepreneurs to get their entrepreneurial projects off the ground. However, venture capital investments are characterized by high levels of information asymmetry. Venture capital investors act as outside investors who are confronted with an informational disadvantage (Admati and Pfleiderer 1994; Cornelli and Yosha 2003). They are faced with the challenges of hidden information (Jensen and Meckling 1976) and adverse selection risks (Akerlof 1970) when they try to decide in which company to invest. The quality of potential investment targets varies greatly and it can be assumed that most times the founders of entrepreneurial ventures are at an informational advantage vis-à-vis the investor because they have superior knowledge about the quality of their business (Leland and Pyle 1977). Additionally, a similar argument holds for founders seeking an investor. Founders give up some of their decision power and independence by taking in outside investors. Ideally, a venture capital investor not only provides capital for the startup but also acts as a trusted partner and advisor. Investors can gain substantial influence over the startup's decisions by taking board seats after an investment. Some investors even force out the founder, if there is disagreement over the development of the business (Chen and Thompson 2015; Dubocage and Galindo 2014). So mutual trust plays an outstanding role in the investment initiation stage. Consequently, both investors and founders may shy away from some investments due to information asymmetries and a lack of trust in the counterparty resulting in the prevention of some otherwise profitable investments.

This paper contributes to the empirical literature about the effect of social ties on mitigating agency conflicts and information asymmetry in business relationships. It explores one specific attribute of startup founders and venture capital firm partners - their educational background - that potentially helps to mitigate the issues related to information asymmetry in venture capital investments. Why should university affiliations matter in a venture capital funding relationship? This paper argues that they offer two distinct channels of interest. First, university attendance shapes and signals the human capital of founders. Top-university affiliations of founders help investors to identify better deals and make more informed investment decisions. There is extant evidence for the value of attending high-quality universities in other corporate finance settings (Fuchs et al. 2022; King et al. 2016; Miller et al. 2015; H. Li et al. 2011; Gottesman and Morey 2006; Chevalier and Ellison 1999a) in support of a positive role of high-quality education for economic outcomes. Second and more importantly for this paper, university graduates become part of universities' alumni networks. Gompers et al. (2020) report that the largest share of deal flow originates from the network of the partners at a VC firm. Thus, alumni networks should be one important source of deal flow in venture capital. Alumni networks as a specific form of social capital foster generalized trust, offer effective penalty and reward mechanisms, and improve information flow between its members. Other authors have found educational ties to be of value in various corporate finance and business settings (Engelberg et al. 2012; Cohen et al. 2010; Cooney et al. 2015; Fuchs et al. 2021; Gompers et al. 2016). A key contribution of this paper is that it scrutinizes the value of educational ties between founders and investors over the whole venture capital funding lifecycle: from the effect on the initial matching between startup and venture capital firm itself, over how they affect the depth of the level of involvement of the investor during the funding relationship, all the way to the effect on the eventual startup performance and investment exit success of the investor.

The basis for the empirical analysis in this paper is a unique and novel international data sample comprising 42,101 first-time investments by 2,753 unique VC firms in 18,588 unique startups that involve 29,491 founders and 9,921 VC partners. The sample relies on data from Crunchbase and LinkedIn and covers domestic and international deals by both U.S. and European VC firms between 2000 and 2020. Thanks to the combination of the two relatively novel data sources, the sample covers more individuals and unique investments than any prior research analyzing related forms of social ties in venture capital (e.g. Sunesson 2009; Bengtsson and David H Hsu 2010; Bengtsson and David H. Hsu 2015; Gompers et al. 2016) and is, therefore, less likely to suffer from a sample selection bias. It is also the first one to include VC firms and startups outside of the United States. In addition to the sample of actual investments, the identification strategy in this paper relies on a set of 4,696,760 counterfactual observations acting as a plausible control group in the matching analysis. This is necessary because it is impossible to observe investments that could have been taken by investors but ultimately did not materialize. Due to the broad coverage of individuals and their university affiliations the sample also allows for exploring the effect of educational ties at different granularity levels. By differentiating between educational ties stemming from top and non-top universities, as well as between top U.S. and top European universities, it is possible to show whether the value of educational ties is dependent on their origin.

The empirical results on the effect of university affiliations on the likelihood of a match between a startup and a VC firm can be summarized as follows. First, the analysis of individual characteristics confirms that the likelihood of investment is roughly 5% higher when a founder attended a top university. This effect, however, is only statistically significant for top U.S. university graduates. Second, when investors and founders share an alumni network the likelihood of an investment increases by 23.6% relative to the baseline probability of investment. This statistically and economically significant effect

can be confirmed for top and non-top university based educational ties and is present for U.S. and European university ties underscoring the value of alumni networks for any kind of university. Third, results show that the educational ties are more valuable the more exclusive they are. At the same level of exclusivity, top-university ties are more valuable for the investment decision than non-top university ties. The results on matching are robust to several alternative model specifications including investor and startup fixed effects, to sub-sample analyses, and to alternative counterfactual methodology. Further results analyzing the effect of educational ties on the funding relationship conditional on an investment confirm that educational ties influence the scope and timing of investments, as well as exit outcomes. When the investment partner managing a deal on the VC firm side and at least one of the founders attended the same university the likelihood of the VC firm acting as the lead investor is 37% percent higher and the likelihood of taking a board seat is 115% higher. Additionally, investors are willing to take riskier investments in the presence of educational ties. Educational ties are related to investments in on average younger startup companies and increase the likelihood of investing in the first funding round of a startup. Finally, I also find a positive effect of educational ties on investment outcomes. Investments involving educational ties between the VC investment partner and the founding team are about 40% more likely to lead to an IPO.
The remainder of this paper is structured as follows. First, section 4.2 lays out the theoretical background of why university affiliations should play a role in venture capital investments, highlights relevant related research, and develops testable hypotheses. Next, section 4.3 introduces and summarizes the data sample, as well as central variables and explains the empirical identification strategy. Then, section 4.4 presents and discusses the results of the empirical analysis and goes over the potential limitations of the empirical findings. Finally, section 4.5 concludes.

4.2 Background, Related Literature, and Hypotheses

This paper explores the effect of university affiliations of founders and investors in mitigating frictions in venture capital funding relationships. University affiliations might reduce information asymmetry between founders and investors via two distinct channels affecting the whole lifecycle of venture capital investments. Attending a certain university can, on the one hand, act as a quality signal for human capital (see e.g. Arcidiacono et al. 2010) and, on the other hand, make up a large part of the social capital (see e.g. James S. Coleman 1988; Seibert et al. 2001) of the university's alumni. This paper focuses on the latter channel but also explores the former one to rule it out as the driving

factor behind the main results.
The first channel works as follows. Academic institutions might act as an easily observable quality signal for individuals' capabilities and skills. Among other aspects, universities differ in their teaching paradigms, research quality, admission selectivity, and specialization areas. This means that self-selecting to attend a certain university is an observable reflection of an individual's character and preferences. Furthermore, strict admission policies of top universities ensure that incoming attendants are on a similar intellectual level[1] when they enter the institution. Before individuals graduate from an academic institution the idiosyncratic university curriculum then expands the subject matter expertise and capabilities of its attendants. It is an old debate in corporate finance in general and venture capital in particular whether it is more important to bet on the horse (the business) or the jockey (the founding team) (see e.g. Kaplan et al. 2009). Gompers and Lerner (2001) provide anecdotal evidence that many venture capital investors place 'their bets' on the team, not the business.[2] This line of argumentation is supported by related literature that finds positive relationships between high-quality education and career or labor market outcomes and firm performance. For example, Chevalier and Ellison (1999a) find that mutual fund managers that attended higher-SAT-score undergraduate institutions have systematically higher risk-adjusted excess returns and Miller et al. (2015) report that Ivy-League-educated CEOs are associated with better firm performance. Similar findings are reported by King et al. (2016) who report that high-quality CEO education is positively related to bank performance. Therefore, it is a valid assumption that VC investors take into account the information they can learn about the unobservable founding team characteristics from the observable educational track record of potential investees to gauge their abilities.

H1: Founders affiliated with a top university raise investment likelihood

The second channel focuses on educational ties and is the main focus of the exploration in this paper. University alumni networks as a special form of a social network are an important part of an individual's social capital. If a founder and an investor attended the same university, they are part of the same alumni network, irrespective of whether they attended the university at the same time or obtained the same degree. Granovetter (2005) highlights three mechanisms explaining why social networks should affect economic

[1] Several related studies use American standardized undergraduate admission (SAT scores) or graduate admission (GMAT) test scores to proxy for cognitive abilities of individuals (e.g. Fuchs et al. 2022; H. Li et al. 2011; Gottesman and Morey 2006; Chevalier and Ellison 1999a).

[2] There is an old saying in venture capital embracing the idea that the founding team is more important than the initial business idea: "You can have a good idea and poor management and lose every time. You can have a poor idea and good management and win every time." (D. Gladstone and L. Gladstone 2002, pp. 91-92)

outcomes. First, they improve the quality and flow of information. Second, their members are incentivized by social reward and punishment mechanisms enforcing 'good' behavior. And third, they foster generalized trust[3] between otherwise unknown individuals. In support of the argument that trust plays an important role in venture capital investments, Bottazzi et al. (2016) report empirical evidence showing that a higher level of generalized trust is associated with a higher likelihood of investment in venture capital. So in short, belonging to the same alumni network should reduce information asymmetry, moral hazard, and adverse selection issues (Kuhnen 2009).

Several related studies find empirical evidence for the role of educational ties in business relationships in other settings. For example, Engelberg et al. (2012) find that social ties between executives of banks and firms are positively related to lower interest rates of the firms' commercial loans. Educational ties in particular are found to be four times more valuable than other forms of social ties. They argue that interest rates are lower because banks are able to make more informed loan decisions due to improved information flow and quality. In the context of mutual funds, Cohen et al. (2010) analyze educational ties between sell-side analysts and senior management. They find that in the presence of educational ties analysts outperform on their stock recommendations, which the authors attribute to the ability to gather superior information via the educational ties. Further, Cooney et al. (2015) find that educational ties help investment banks to secure underwriting business. Banks with educational ties to the IPO firm are more likely to be included in the syndicate, in a more senior role, and with higher fees. Fuchs et al. (2021) explore the role of educational ties in sourcing private equity deals. They find that educational ties between fund managers and CEOs are positively related to winning buy-out deals in a competitive setting. In venture capital, Gompers et al. (2016) scrutinize the formation of investment syndicates of venture capitalists. Among other similarity characteristics, they find that investors are more likely to form a syndicate when they graduated from the same university. In sum, the literature supports the notion that educational ties are an important factor in the formation of business relationships. Thus, in the case of venture capital, it can be assumed that a shared educational background between founders and VC partners increases the likelihood of investment.

H2: Educational ties between founder and investor increase the likelihood of investment

The investment decision alone is only one aspect characterizing the funding relationship between venture capital firms and startups. Hegde and Tumlinson (2014) provide a formal model and initial empirical evidence that socially close individuals should be able

[3]Generalized trust is based on general prior beliefs about the behavior of a random member of an identifiable group of individuals, which in this case is the group of university alumni (James S Coleman 1994).

to work better together. If educational ties do mitigate information asymmetries and improve collaboration between founder and investor it should be assumed that the scope of the funding relationship differs from investments without educational ties. In a related study, Bengtsson and David H. Hsu (2015) analyze the role of co-ethnicity between investor and founder empirically. They argue that belonging to a 'tight' social network improves collaboration between individuals and find evidence that investors are more involved in their investments when the founder is co-ethnic. It is reasonable to assume that the same holds for educational ties. There are several ways for an investor to be more involved in the startup. Venture capital firms can act as lead investors spearheading the investment syndicate. This role usually entails being the largest shareholder in the startup company and representing the investment syndicate as well as interacting with the startup with higher frequency and intensity (Barry et al. 1990; Megginson and Weiss 1991). Gorman and Sahlman (1989) report survey results among venture capitalists that show that investors spent ten times more time with investments when they act as lead investors. Further, investors can take over board seats to frequently interact with the startup and shape its strategy (Garg and Furr 2017; Rosenstein 1988). And finally, investors can participate in follow-on funding rounds to stay invested in the company over its full lifecycle.

H3: Educational ties between founder and investor are associated with a larger scope of the funding relationship

In addition, information asymmetries are usually highest for younger companies and first founding rounds. Cochrane (2005) finds that investments in later funding rounds are consistently related to lower investment risk for venture capital investors. Given the argument that educational ties improve information flow and increase trust, investments in the first funding round as well as investments in younger companies should be more likely in the presence of educational ties.

H4: Investors are more likely to undertake riskier investments in the presence of an educational tie

The ultimate goal of a VC firm is to increase the value of its invested capital by eventually exiting all investments during a fund's lifetime. Thus, the funding relationship usually ends with an exit, which in the most successful venture capital investments happens via IPO. There are two competing views on how educational ties might relate to investment outcomes. On the one hand, if all arguments laid out above are confirmed educational ties should be related to better operative startup performance and therefore exit success. In the presence of educational ties, investors should be able to make more informed investment decisions, i.e. select better startups in the first place, and work more effectively with the startup, i.e. add more value over time. On the other hand, educational ties could also produce favoritism and social conformity, which might lead to e.g. inefficient decision-making or lower due diligence standards (Fracassi 2017; Ishii and Xuan 2014). In the context of venture capital syndication, Gompers et al. (2016) find evidence for a negative relationship between syndicates comprised of similar venture capitalists and their performance. They call the effect the 'cost of friendship' and argue that homophily among similar venture capitalists leads to worse investment outcomes. Bengtsson and David H. Hsu (2015) also find a negative effect of co-ethnicity between founders and VC partners on the likelihood of a successful exit. Both points of view have their merit and thus the dominating effect of educational ties on investment success could go in either direction.

H5a: Educational ties increase the likelihood of success of venture capital investments

H5b: Educational ties decrease the likelihood of success of venture capital investments

4.3 Data and Variables

4.3.1 Sample Construction and Data Collection

The starting point of the data collection process is information about venture capital deals from Crunchbase, which is still a novel source of entrepreneurial finance data for academic research (e.g. Gaddy et al. 2017; Cumming et al. 2014; Alexy et al. 2012). The Crunchbase database offers a broad range of information surrounding funding rounds, investors, startup characteristics, and detailed biographical data about people involved in deals. In fact, Retterath and Braun (2020) compare different venture capital databases and find that Crunchbase is among the data providers with the best coverage of venture capital investments. I begin with collecting all venture capital investments from 2000 to the end of 2020[4] conducted by VC firms located in the United States of America or Europe[5] in worldwide startup companies. The sample is on the individual investment level, i.e. each observation represents an investment by a VC firm in a startup company, which means that funding rounds comprising more than one VC firm as investors will occur in the sample several times. As the main focus of this paper is on the initial

[4]While the sample period for the main analysis is restricted, information on deals before the year 2000 are considered for the construction of some variables such as *VC Experience* nevertheless.

[5]The following European countries are included in the sample: Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Greece, Ireland, Italy, Luxemburg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland

strategic investment decision, whether or not to invest in a startup, the sample only covers the first investment a VC firm makes in a specific startup company. Investments by the same VC firm in the same startup company in follow-on funding rounds are omitted from the sample. Additionally, investments for which some information (e.g. industry classification or founding team) for the empirical analysis is not available are not included in the sample. This leads to a sample of 42,101 investments in 18,588 unique companies conducted by 2,753 VC firms. Figure 4.1 graphically illustrates the geographical sample distribution of startups and VC firms. Roughly two-thirds of the VC firms (1,989) in the sample are from the United States of America, and the rest (764) is from Europe. For startups, there is a similar share of U.S.-based companies. 12,643 startups are located in the United States of America, 3,919 are located in Europe, and 2,026 are located outside of Europe and the United States of America. The broad geographical and temporal coverage of the sample is a unique benefit of this study compared to earlier related studies.[6]. This paper focuses on the educational ties of founders and VC partners. Thus, for the analysis, it is of utmost importance to first identify all persons involved in each investment who fall in these two categories. I utilize Crunchbase's information on job titles to identify founders and VC partners via simple text string matching. A person is classified as a founder if the person is linked to a startup and his or her job title contains the text *'founder'* or *'founding'*. To be classified as a VC partner, a person has to be linked to a VC firm and his or her job title needs to contain the text *'partner'*, *'director'*, *'principal'*, or *'managing'*. For all persons identified in this manner, the available educational track record on Crunchbase is added to the sample.

Even though Crunchbase collects its data from several sources[7], there is still a significant number of persons in the sample for which Crunchbase does not have any record of their educational background. To ensure maximum coverage of educational backgrounds and to alleviate concerns regarding a biased sample, the sample is complemented with data from LinkedIn profiles. LinkedIn is an online platform for professional networking allowing members to share their educational and professional history, which has been

[6]For example, in two unpublished working papers Sunesson (2009) and Bengtsson and David H Hsu (2010) both analyze some aspects of university affiliations in venture capital, however, their samples are severely limited in geographic and temporal scope due to data availability, which makes a selection bias very likely. Sunesson (2009) only covers 735 investment rounds of 456 U.S.-based venture capital firms in 651 U.S.-based portfolio companies. Further, all investments are from the year 2002. Bengtsson and David H Hsu (2010) only include 1,780 investments from 283 and 955 U.S.-based VC firms and startups, respectively.

[7]Crunchbase sources the data via three channels: 1) Upon registration anyone from the community can submit information that is then reviewed before it goes public. 2) Machine Learning models paired with web crawlers automatically collect relevant information to validate or extend the database. 3) An in-house data team manually expands and curates the database.

Figure 4.1.: Graphical Sample Overview of Locations of VC firms and startups

This figure depicts the geographical distribution of the startups and VC firms included in the sample. VC firms are represented by black triangles, startups are represented by grey crosses. If more than one organization is at the same location, the marking is less translucent.

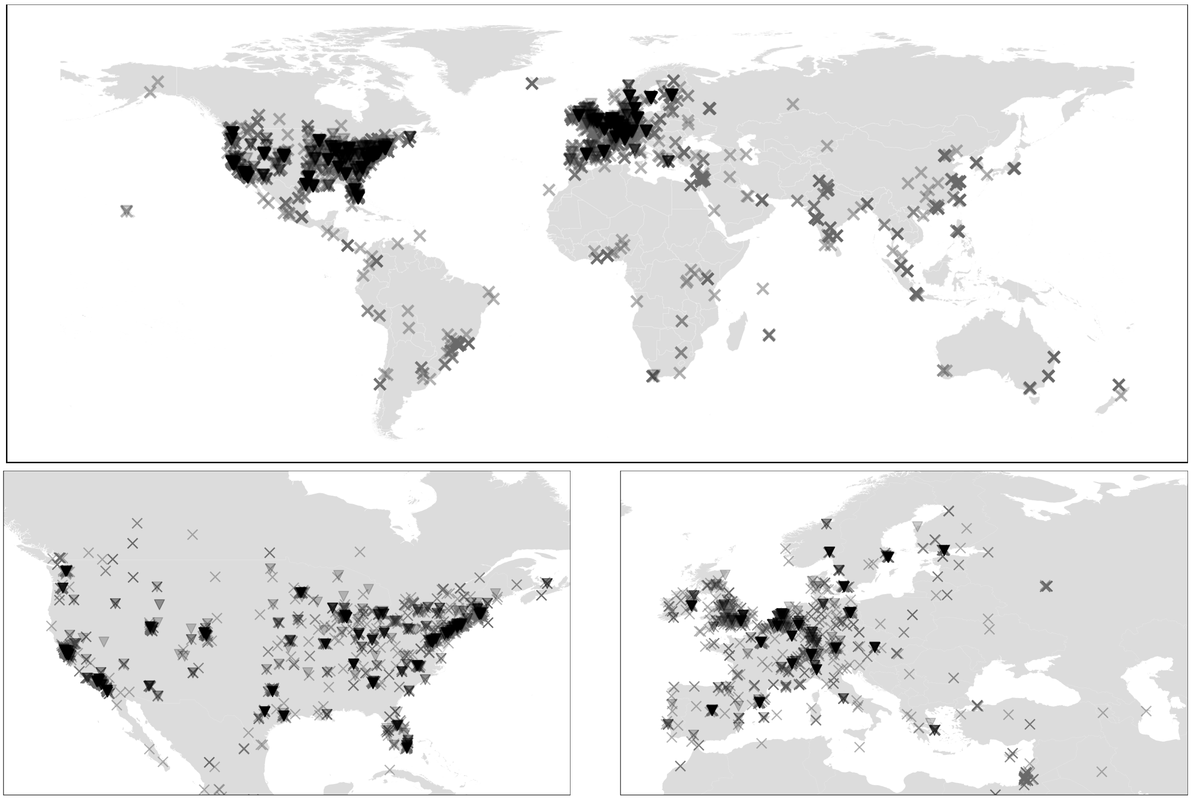


Table 4.1.: Summary of the Sample Scope

This table summarizes the scope of the sample in terms of the number of included investments, startup companies, VC firms, and individuals. As several VC firms can invest in the same startup company, the number of investments is larger than the number of startup companies. Some founders also act as VC partners and vice versa. That is why the sum of the number of founders and the number of VC partners is larger than the number of unique individuals. If an individual holds more than one degree from the same university only one affiliation to this university is counted.

Number of ...	
... unique investments (VC firm-company matches)	42,101
... unique startup companies	18,588
... unique VC firms	2,753
... unique individuals	38,452
... founders	29,491
... VC partners	9,921
... university affiliations	58,502

used as a (complimentary) data source in entrepreneurial finance research before (e.g. Gompers et al. 2020; Banerji and Reimer 2019; Chahine et al. 2019). By combining LinkedIn and Crunchbase data, this study can rely on a unique sample comprising 38,452 individuals of which 29,491 act as founders and 9,921 act as VC partners. As some individuals act both as VC partner and founder in different investments, the sum of founders and VC partners is higher than the overall number of individuals in the sample. The information on 9,498 of these individuals stems from LinkedIn, while the information on the other 28,954 individuals comes from Crunchbase. As a result and a second key benefit of this study, the sample covers a significantly higher number of individuals compared to other related studies dealing with individuals involved in VC investments (e.g. Gompers et al. 2016; Bengtsson and David H. Hsu 2015).[8] Overall, the 38,452 individuals in the sample have 58,502 university affiliations. Table 4.1 summarizes the scope of the sample.

4.3.2 University Affiliations of Individuals Involved in Investments

Next, I focus on the key empirical challenge of unmistakably identifying the university affiliations of every individual in the sample, which is a prerequisite to also identifying educational ties. In this context, there are two drawbacks of using data from both

[8] Specifically, the sample in Gompers et al. (2016) includes 3,510 VC partners and the sample in Bengtsson and David H. Hsu (2015) covers 5,093 founders and 2,361 VC partners.

LinkedIn and Crunchbase. First, there is no unique identifier connecting educational institutions between the two data sources, and second, universities are not always uniquely identifiable even within each of the two data sources. While the second issue is more severe for the noisy user-entered LinkedIn data, it is also of albeit smaller concern in the Crunchbase data. For example, the well renowned German University *TU München* appears under several aliases in the data collected from LinkedIn[9] but also has two name instances on Crunchbase[10]. To overcome both issues, this paper relies on fuzzy string matching algorithms to match every name variant of a university to its most frequent alias. Fuzzy string matching is a technique that allows finding text strings that match other text strings approximately, but not exactly. I implement the basic fuzzy string matching algorithm via the python package *TheFuzz* including its Levenshtein distance (Levenshtein 1966) option. Levenshtein distance measures how many editing steps are required to transform one text string into another one, which is a common way to measure the similarity of two text strings. I combine this simple distance measure with other text pre-processing techniques such as string cleaning (to remove excess spaces and transform special characters etc.), tokenization (to get individual university name components), and stop word removal (to remove common terms not bearing relevant information in this context such as *'university'* or '*school'*) and different fuzzy matching logics[11] to extract likely university name matches above a pre-defined similarity threshold. All likely matches identified by the algorithm are then manually validated to ensure a high level of accuracy of the university affiliation data in the sample. Table 4.2 summarizes the university affiliations of both, founders and investors. A substantial share of all founders and investors is affiliated with well-known universities. For example, 4.97% and 3.89% of all founder affiliations and 6.93% and 7.75% of all investor affiliations can be attributed to Stanford University and Harvard University, respectively. The 30 most frequently represented universities among founders combined make up almost 35% of all university affiliations. On the investor side, the concentration on a few institutions is even stronger. Over 47% of university affiliations can be attributed to investors' 30 most frequent universities.

[9] e.g. *Technische Universität München, Technische Universitaet Muenchen, TU Munich, TU Muenchen, Technical University Munich*

[10] *Technical University of Munich* and *Technische Universität München*

[11] The *TheFuzz* package offers four underlying logics for matching: 1) Ratio uses pure Levenshtein distance 2) Partial Ratio matches based on best substrings 3) Token Sort Ratio tokenizes the strings and sorts them alphabetically 4) Token Set Ratio tokenizes the strings and compares the intersection and remainder.

Table 4.2.: University Affiliations of Founders and Investors

This table presents the 30 most frequent university affiliations of founders in Panel A and of investors in Panel B. Top universities are as defined in the main text in section 4.3.2. If an individual attended a university for more than one degree, this counts as one affiliation only.

Panel A: Founders with affiliation to ...				**Panel B:** Investors with affiliation to ...			
Rank	**University**	**N**	**%**	**Rank**	**University**	**N**	**%**
1	Stanford University	2,164	4.97%	1	Harvard University	1,157	7.75%
2	Harvard University	1,695	3.89%	2	Stanford University	1,035	6.93%
3	Massachusetts Institute of Technology - MIT	1,215	2.79%	3	University of Pennsylvania	521	3.49%
4	University of California, Berkeley	1,009	2.32%	4	Massachusetts Institute of Technology - MIT	337	2.26%
5	University of Pennsylvania	802	1.84%	5	University of California, Berkeley	316	2.12%
6	Columbia University	579	1.33%	6	Columbia University	315	2.11%
7	Tel Aviv University	443	1.02%	7	Northwestern University	252	1.69%
8	Cornell University	436	1.00%	8	University of Chicago	202	1.35%
9	University of Cambridge	398	0.91%	9	Yale University	196	1.31%
10	Northwestern University	396	0.91%	10	Cornell University	195	1.31%
11	New York University	388	0.89%	11	Princeton University	186	1.25%
12	University of Southern California	386	0.89%	12	Dartmouth College	186	1.25%
13	University of Michigan	372	0.85%	13	University of California, Los Angeles (UCLA)	179	1.20%
14	University of California, Los Angeles (UCLA)	365	0.84%	14	University of Oxford	169	1.13%
15	Carnegie Mellon University	365	0.84%	15	INSEAD	157	1.05%
16	University of Oxford	365	0.84%	16	Duke University	152	1.02%
17	Yale University	361	0.83%	17	University of Michigan	150	1.00%
18	California State University	359	0.82%	18	University of Cambridge	145	0.97%
19	The University of Texas at Austin	352	0.81%	19	New York University	145	0.97%
20	Princeton University	280	0.64%	20	University of Virginia	140	0.94%
21	Duke University	278	0.64%	21	California State University	136	0.91%
22	University of Illinois at Urbana-Champaign (UIUC)	278	0.64%	22	Georgetown University	124	0.83%
23	University of Chicago	270	0.62%	23	The University of Texas at Austin	104	0.70%
24	Dartmouth College	239	0.55%	24	University of Southern California	90	0.60%
25	University of Washington	236	0.54%	25	London Business School	89	0.60%
26	Brown University	220	0.50%	26	London School of Economics and Political Science (LSE)	88	0.59%
27	Technion	220	0.50%	27	Boston University	79	0.53%
28	University of Wisconsin - Madison	198	0.45%	28	University of Illinois at Urbana-Champaign (UIUC)	75	0.50%
29	Boston University	192	0.44%	29	Brown University	72	0.48%
30	INSEAD	192	0.44%	30	University of Wisconsin - Madison	71	0.48%
	Others	28,516	65.45%		Others	7,870	52.70%
	Total number of affiliations	43,569	100.00%		Total number of affiliations	14,933	100.00%
	Top	14,796	33.96%		Top	6,774	45.36%
	Top US	10,097	23.17%		Top US	5,181	34.69%
	Top European	4,699	10.79%		Top European	1,593	10.67%

The data collected on individuals and universities are used to construct two general sets of variables: At the individual level and the VC-firm-startup dyad level. For the individual level, I create dummy variables (*Founder: Top, Top US, Top European* and *Investor: Top, Top US, Top European*) indicating whether any of the individual founders or investors attended any top U.S., or top European university, respectively. I rely on the classification used in Gompers et al. (2016) to identify top U.S. universities.[12] Considering that most European countries have less pronounced 'elite' university systems in comparison to the U.S., appropriately identifying top European universities is not as straightforward. University rankings such as the established Times Higher Education ranking (THE) that are used in related research (e.g. Fuchs et al. 2021) focus heavily on research output and teaching quality. However, since I am primarily interested in alumni networks and signaling effects stemming from attending the 'right' university, a classification based on these rankings would not result in a classification scheme for European universities directly comparable to the U.S. classification. Thus, I instead rely on the top entrepreneurial university ranking published by EU Startups and the business school ranking published by the Financial Times, to identify the top universities in Europe that are recognized in the venture capital and startup community. These rankings put a stronger emphasis on factors such as alumni salaries and employability, which is closer in spirit to the U.S. system of elite universities. The resulting list comprises 67 universities classified as top in the 17 European countries included in the sample.[13]
While the individual level variables for founders and investors do not change for all

[12]The list includes the Ivy League schools (Brown University, Columbia University, Cornell University, Dartmouth College, Harvard University, Princeton University, University of Pennsylvania, and Yale University) and other top U.S. institutions (Amherst College, Caltech - California Institute of Technology, Duke University, Massachusetts Institute of Technology - MIT, Northwestern University, Stanford University, University of California, Berkeley, University of Chicago, and Williams College).

[13]The list includes Aalto University, Aarhus University, Autonomous University of Barcelona, Bocconi University, Charles III University of Madrid, Copenhagen Business School, Delft University of Technology, École Polytechnique, École Polytechnique Fédérale de Lausanne, EM Lyon Business School, Erasmus University Rotterdam, ESADE, ESCP Business School, ESSEC Business School, ETH Zurich, Freie Universität Berlin, Ghent University, HEC Paris , HHL Leipzig, IE Business School, Imperial College London, INSEAD, Karlsruhe Institute of Technology, KTH Royal Institute of Technology, Leiden University, London Business School, Ludwig Maximilian University of Munich, LUISS Guido Carli University, Norwegian University of Science and Technology, Polytechnic University of Catalonia, Polytechnic University of Milan, RWTH Aachen University, Sapienza University of Rome, Sciences Po Paris, Stockholm School of Economics, Technical University of Berlin, Technical University of Denmark, Technical University of Munich, Lund University , The London School of Economics and Political Science (LSE), Trinity College Dublin, TU Wien, UCL, Universidade Nova de Lisboa, University College Dublin, University of Amsterdam, University of Bologna, University of Cambridge, University of Cologne, University of Copenhagen, University of Edinburgh, University of Groningen, University of Helsinki, University of Leuven, University of Mannheim, University of Navarra, University of Oslo, University of Oxford, University of Porto, University of St. Gallen, University of Vienna, Utrecht University, Vlerick Business school, WHU - Otto Beisheim School of Management, and WU Vienna.

of their respective investment relationships, the VC-firm-startup dyad level variables are determined newly for each investment pairing. Again, I construct several dummy variables. *Both: Top, Top US, Top European* indicate whether both, anyone from the founding team and anyone from the investor team, attended any (but not necessarily the same) top university with one, and zero otherwise. For example, if one founder went to Stanford University and one investor went to Harvard University this dummy variable would be equal to one. Finally, to identify whether there is an educational tie, i.e. anyone of the founders and anyone of the investors have a shared university affiliation, I introduce *Both: Same*. This dummy is only equal to one if at least one of the founders and anyone of the partners at the VC firm attended the same university, and zero otherwise. Additionally, in order to find out whether or not there is a difference between attending the same top (or non-top) university, I also introduce *Both: Same Top*, *Both: Same non-Top*, *Both: Same Top US*, and *Both: Same Top European*, which are constructed analog to *Both: Same*, but only take into account the relevant subset of university affiliations.

This study is built around the individuals involved in the standard decision-making process in the VC industry regarding the two-sided deal-sourcing process (from the point of view of a VC firm) or the two-sided investor-seeking process (from the point of view of a founder). Gompers et al. (2020) provide empirical confirmation, of what is considered standard procedure in the VC industry: The largest share of deal flow originates from the network of the VC partners at a VC firm. While the overall investment decision is usually taken at a firm-wide partner meeting, as a rule, one partner is regularly acting as the investment partner. This investment partner takes care of the initial screening and contact with the founding team before promising opportunities are brought to the other partners at the firm. Further, the investment partner acts as the link between the VC firm and the startup company at least until the deal is closed.

Thus, it is natural to assume that any effect of a shared educational background between investor and founder should be more pronounced when it stems from the connection with the investment partner. Consequently, this study differentiates between a '*narrow*' educational tie between the founding team and the investment partner and educational ties in the broader sense, i.e. between the founding team and anyone of a VC firm's partners. To identify which of the partners at the VC firm acts as the investment partner in a specific investment the paper relies on the information provided by Crunchbase.

4.3.3 Counterfactual Investment Approach

Ideally, it would be possible to observe deals that were considered by VC firms but ultimately did not materialize, as well as to gather details on any instance where investors were solicited by startups but the contact eventually did not result in a funding relationship. However, no such private information is available for this paper. Thus, in order to analyze the effect of university affiliations and educational ties on the likelihood of a match between a startup and a VC firm, a set of plausible counterfactual investments needs to be constructed. These counterfactual investments serve as a control group, that makes it possible to scrutinize the significance of educational ties for the matching of startups and VC firms. I follow the general counterfactual approach laid out by literature dealing with related issues (e.g. Fuchs et al. 2021; Gompers et al. 2016; Bengtsson and David H. Hsu 2015; Corwin and Schultz 2005), by developing the set of plausible counterfactual investments from the observable investments that were consummated by other investors.

For each actual investment, I identify all potential investments in the sample that the investor in principle could have chosen as an alternative. Each counterfactual investment has to fulfill three criteria to qualify as a plausible alternative investment. First, the counterfactual investment has to be in a startup located in the same country as the actual investment's startup. For U.S.-based startups, this requirement is tightened to the same state. Second, the counterfactual investment must take place within six months before or after the actual investment. Third, the counterfactual investment has to be in a startup within the same industry group as the actual investment. For example, on January 11^{th} in 2018 U.S.-based VC firm Scale Venture Partners invested in Unbabel, a startup based in Portugal developing an AI-based language operations platform for B2B customers. Two other Portugal-based B2B software startups closed funding rounds in the 6 months before and after the investment in Unbabel: Codacy and Prodsmart. These two are consequently considered plausible counterfactuals that Scale Venture Partners in principle could have invested in. Following this approach for all actual investments leads to in sum 4,696,760 counterfactual investments, which means on average there are around 111 counterfactuals per actual investment.[14] While the procedure described above results in a high number of reasonable counterfactuals, by design it cannot include any startup that was not funded by anyone in the first place or any follow-on funding rounds that did not attract enough investors willing to invest. However, this is no drawback for the

[14]To alleviate concerns about the counterfactual approach stemming from the fact that some investments have only a few counterfactuals while some have over 200 plausible counterfactuals, in section 4.4.1 I include a robustness check that limits the counterfactuals to one per actual investment. Results are robust to this alternative counterfactual selection approach.

identification strategy in this paper. By only including 'materialized' investments, it is reasonable to assume that every counterfactual included in the sample represents an investment opportunity that would bear the scrutiny of a due diligence process. Hence, fewer factors such as a startup's quality influence the likelihood of investing that must be controlled for. Nevertheless, to make sure that my results are not distorted by an omitted variable bias, I include a robustness check in section 4.4.1 that includes startup company fixed effects to control for all idiosyncratic startup company characteristics (see models (3) and (4) in table 4.8).

Table 4.3 shows crosstabulations for shared university affiliations and actual and counterfactual investments to give a first indication of the role of educational ties. If a shared university background is a factor positively contributing to the likelihood of an investment, the case should be overrepresented in the actual investment sample when comparing it with the sample of counterfactuals. Panel A uses the most general variable *Both: Same* introduced above that captures all educational ties to split the sample. There are 14,401 investments in the main sample of actual investments that exhibit a shared educational background between founders and investors. The resulting share of 34.21% is distinctly higher than the equivalent share in the counterfactual sample (29.40%) which is first indicative evidence that a shared university affiliation plays a role in the matching process in venture capital deals. Panel B and Panel C offer the same descriptive analysis for *Both: Same Top* and *Both: Same non-Top*, respectively. The same general pattern can be observed for these two cases as well. The share of actual investments with a top university educational tie is 13.5% higher for the actual investments (27.61%) compared to the counterfactual investments (24.31%). Even though the absolute number of educational ties that are not related to top universities is significantly lower (2,777 cases of non-top educational ties vs. 11,624 cases of top educational ties) the percentage difference is even higher than in the case *Both: Same Top*. The share of actual investments with a non-top educational tie (6.60%) is almost 30% higher than the corresponding share in the counterfactual sample (5.09%). This might indicate that these relatively rare educational ties stemming from non-top universities have a more pronounced effect on the likelihood of investment.

4.3.4 Other Variables

Table 4.4 summarizes the variables introduced above as well as additional ones required for the empirical analysis and provides the definitions for all variables. Besides the variables already discussed above, there are five dependent variables (see Panel A) used in section 4.4 for the empirical analysis. The main dependent variable, *Match*, is a dummy

Table 4.3.: Matches between startups and VC firms and shared university affiliations

This table shows crosstabulations for educational ties (i.e. shared university affiliations between founders and investors) and actual and counterfactual investments. Panel A does not distinguish between top or non-top educational ties. Panel B only shows top-university-based educational ties. Panel C only counts non-top-university-based educational ties. Top universities are as defined in the main text in section 4.3.2.

Panel A: Same university

	Both: Same		
Investment	**No**	**Yes**	Sum
Counterfactual	3,315,746	1,381,014	4,696,760
	(70.60%)	(29.40%)	(100%)
Actual	27,700	14,401	42,101
	(65.79%)	(34.21%)	(100%)
Sum	3,343,446	1,395,415	4,738,861
	(70.55%)	(29.45%)	(100%)

Panel B: Same Top University

	Both: Same Top		
Investment	**No**	**Yes**	Sum
Counterfactual	3,554,932	1,141,828	4,696,760
	(75.69%)	(24.31%)	(100%)
Actual	30,477	11,624	42,101
	(72.39%)	(27.61%)	(100%)
Sum	3,585,409	1,153,452	4,738,861
	(75.66%)	(24.34%)	(100%)

Panel C: Same non-Top University

	Both: Same non-Top		
Investment	**No**	**Yes**	Sum
Counterfactual	4,457,574	239,186	4,696,760
	(94.91%)	(5.09%)	(100%)
Actual	39,324	2,777	42,101
	(93.40%)	(6.60%)	(100%)
Sum	4,496,898	241,963	4,738,861
	(94.89%)	(5.11%)	(100%)

equal to one for the actual investments, and zero for all counterfactual investments. Furthermore, in the empirical part, I also analyze the effect of educational ties on the timing and scope of the 42,101 actual investments, to find out if the nature of the relationship between startups and VC firms differs from investments without a shared educational background. For the analysis of the timing of investment, I introduce two variables. The first one is *Age of Startup* which is defined as the natural logarithm of the startup's age in years at the time of investment. The second variable to analyze the timing of the investments is *First Round*, a dummy variable indicating whether the VC firm invested in the first funding round with one. To examine how the investment scope is influenced by shared educational background this study relies on three variables. First, *Board Seat* is a dummy indicating whether or not a VC firm took a board seat at the startup after an investment. Second, *Lead Investor* is another dummy that measures if the VC firm acts as the lead investor for the investor syndicate. Third, I construct *Number of Rounds* which is a count variable measuring the number of the startup's funding rounds the VC firm participated in including the funding rounds after the initial investment that is included in the sample. Finally, I am also interested in whether investments with educational ties perform better or worse than other investments. Thus, I also include the dummy variable *Success* as an independent variable that is equal to one when the investment eventually exited via an IPO, which is widely considered the most lucrative exit channel for VCs (Cumming et al. 2009; Hochberg et al. 2007; Cochrane 2005; Gompers 1996). In addition to the main variables of interest, I construct several control variables (see Panel D) as well. I compute the geographical *Distance* between startup and VC firm headquarters with the location details available on Crunchbase. Based on the postal address available in the Crunchbase database I first retrieve geo coordinates by querying the OpenStreetMap API. Next, I compute the geodesic between the two points as described in Karney (2013) to get the shortest distance between startup and VC firm on the surface of an ellipsoidal model of the earth. For the empirical analysis, I use the natural logarithm of the computed distance in kilometers. To measure past *VC Performance*, I calculate the share of IPOs out of all startups the VC firm has invested in before the respective deal. Thus, *VC Performance* can take values between zero and one. *VC Experience* is the natural logarithm of the number of investment rounds the VC firm has participated in up to the respective investment. *Serial Founder* is a dummy variable equal to one when at least one of the founders has founded another startup before, and zero otherwise. Finally, *Syndicate Size* is a count variable representing the number of unique investors participating in the funding round.

Table 4.4.: Overview and Definition of Variables of the Analysis

This table provides an overview and the definition of all variables used in the regression analyses.

Variable Name	Definition
Panel A: Dependent Variables	
Match	A dummy variable equal to one for actual investments, and equal to zero for counterfactual investments.
Age of Startup	The natural logarithm of the startup's age in years at the time of investment.
First Round	A dummy variable equal to one when the VC firm invested in the startup's first funding round, and zero otherwise.
Board Seat	A dummy variable equal to one when the VC firm took a board seat after the investment, and zero otherwise.
Lead Investor	A dummy variable equal to one when the VC firm acts as lead investor in the funding round.
Number of Rounds	The number of the startup's investments rounds the VC firm participated in.
Success	A dummy equal to one when the investment eventually exited via an IPO.
Panel B: Explanatory Variables: Individual Founders and Investors	
Founder: Top, Top US, Top European	A dummy variable equal to one when at least one of the founders attended any top, top US, or top European university, respectively, and zero otherwise.
Investor: Top, Top US, Top European	A dummy variable equal to one when at least one of the partners at the VC firm attended any top, top US, or top European university, respectively, and zero otherwise.
Panel C: Explanatory Variables: Founder-Investor Dyad	
Both: Top, Top US, Top European	A dummy variable equal to one when at least one of the founders and anyone of the partners at the VC firm attended any top, top US, or top European university, respectively, and zero otherwise.
Both: Same, Same Top, Same non-Top, Same Top US, Same Top European	A dummy variable equal to one when at least one of the founders and anyone of the partners at the VC firm attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise.
Both: Same, Same Top, Same non-Top, SameTop US, Same Top European (narrow)	A dummy variable equal to one when at least one of the founders and the deal's investment partner attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise.
Both: Same, Same Top, Same non-Top (redundant)	A dummy variable equal to one when more than one founder and/or partner at the VC firm attended the same, the same top, the same non-top university, respectively, and zero otherwise.
Both: Same, Same Top, Same non-Top (scaled)	A scaled version of the dummy variable that is constructed by dividing the respective dummy variable by the number of counterfactual investments that entail the same educational tie.
Panel D: Controls	
Distance	The natural logarithm of the distance between startup and VC firm in kilometers.
VC Performance	The number of IPOs divided by the total number of companies the VC firm has invested in before the respective deal.
VC Experience	The natural logarithm of the number of investment rounds the VC firm has participated in up to the respective investment.
Serial Founder	A dummy variable equal to one when at least one of the founders has founded another startup before, and zero otherwise.
Syndicate Size	The number of investors participating in the funding round.

4.4 Empirical Results and Discussion

4.4.1 Investment Decision

The first step in the analysis scrutinizes the role of university affiliations in the matching process between startups and VC firms. To model the likelihood of a match between founder and investor I rely on probit models for the analysis of the cross-sectional sample. The general specification for the regressions in tables 4.5, 4.6, and 4.7 is shown in equation 4.6.

$$Match_{i,j} = \alpha + \beta Education_{i,j} + \gamma Controls_{i,j} + \delta FE(Year_{i,j},\ Industry_i,\ Region_i,\ Stage_i) \tag{4.6}$$

$Match_{i,j}$ is a dummy that is equal to one for actual investments by VC firm j in startup i and zero for all counterfactual investments. $Education_{i,j}$ is a vector of the independent variables of interest regarding the university affiliations of the founders of startup i and the partners of VC firm j. The vector can include the variables described in table 4.4 depending on the individual model specification. To control for various deal, investor, and startup characteristics the specification includes the vector $Controls_{i,j}$ and several fixed effects to rule out an omitted variable bias. $Controls_{i,j}$ includes the four control variables *Distance*, *VC Performance*, *VC Experience* and *Serial Founder*. *Distance* is included to control for the fact the VCs tend to invest more in their geographical proximity which has been documented in related research (Nahata et al. 2014; Tykvová and Schertler 2014; Cumming and Dai 2010). *VC Performance* and *VC Experience* control for the effect that successful VCs tend to have better access to deal flow (Nanda et al. 2020) and the effect of sorting in the market which leads more experienced VCs to invest in better companies (Sørenson 2007). *Serial Founder* is included to control for the performance persistence of serial founders as documented in Gompers et al. (2010). In addition, *year fixed effects* control for time-varying differences in investment patterns and market environments, *industry fixed effects* control for heterogeneity across different startup industries, *region fixed effects* absorb geographical differences due to cultural and institutional aspects, and *stage fixed effects* account for the different levels of information asymmetry in the funding of earlier and later stage startups.

Individual Educational Background

I start the empirical analysis of whether university affiliations impact the likelihood of investment by exploring the explanatory power of individual founder and investor characteristics in isolation. It might be the case that simply having attended a top university serves as a quality signal that increases investment likelihood even in the absence of a shared university affiliation between founder and investor, i.e. the effect would not rely on alumni networks. Table 4.5 reports the marginal effects of the probit models for this first step of the empirical analysis. To interpret the economic significance of the marginal effects it is important to keep in mind the high number of counterfactual investments included in the observations that lead to a baseline (unconditional) probability of an investment in the sample of only 0.89%[15]. Specifications (1) and (3) explore the general effect, while specifications (2) and (4) use a finer classification to contrast differences between U.S. and European universities. Overall, the results confirm that top university affiliations do play a role in the matching between startups and VC firms, i.e. where you go to school matters. Specification (1) focuses on the top-university affiliations of founders and investors. The results show that a top-university affiliation of a founder increases the likelihood of matching by 0.043 percentage points. The effect is highly statistically significant at the 1% level and corresponds to an increase of 4.8% of the investment likelihood compared to the baseline probability. With regard to *Investor: Top*, the reported effect exhibits a negative sign which means that matching with a VC firm where at least one of the partners attended a top university is less likely. More precisely, the likelihood of investment decreases by 0.065 percentage points, which means that it is 7.3% less likely for an investment to materialize when one of the investors went to a top university. In specification (2) the effects are separately analyzed for top U.S. and top European universities, respectively. The results show that the effect found for *Founder: Top* in specification (1) can be fully attributed to top U.S. universities. In specification (2) there is no significant effect for founders with an affiliation to a top European university, while a founder with a top U.S. university background increases the likelihood of matching by 0.049 percentage points. Interestingly, other than for founders the negative effect on the investor side can be observed for both top U.S. (-0.027 percentage points) and top European universities (-0.043 percentage points).

The positive effect found for founders' top-university affiliations might be driven by the general reputation of a top university acting as a quality signal certifying the abilities of a founder or alternatively by the founders' access to the alumni networks of top universities. To further analyze these alternative explanations, specifications (3) and (4) consider the joint educational background of founders and investors, without requiring both to attend the same university for the dummy to take the value of one, yet. I include *Both: Top* to test if there is a more general 'alumni network' effect amongst top universities. For example, if inter-institutional alumni networks do play a role in deal selection it

[15] The unconditional probability is derived by dividing the number of actual investments by the sum of counterfactual investments and actual investments: $42,101/4,738,861 = 0.00888 \approx 0.89\%$.

Table 4.5.: The Effect of Individual Educational Background on Investment

This table reports marginal effects of probit regressions studying the effect of founders' and investors' educational background on the probability of a match between a startup and a VC firm. The sample comprises 4,738,861 observations, consisting of 42,101 factual and 4,696,760 counterfactual investments. The dependent variable is *match*, a dummy variable equal to one for actual investments, and equal to zero for counterfactual investments. *Founder: Top, Top US, Top European* are dummy variables equal to one when at least one of the founders attended any top, top US, or top European university, respectively, and zero otherwise. *Investor: Top, Top US, Top European* are dummy variables equal to one when at least one of the partners at the VC firm attended any top, top US, or top European university, respectively, and zero otherwise. *Both: Top, Top US, Top European* are dummy variables equal to one when at least one of the founders and anyone of the partners at the VC firm attended any top, top US, or top European university, respectively, and zero otherwise. *Distance* is the natural logarithm of the distance between startup and VC firm. *VC Performance* is the VC firm's IPO ratio up to the current deal. *VC Experience* is the natural logarithm of the number of investment rounds the VC firm has participated in up to the current deal. *Serial Founder* is a dummy variable equal to one when at least one of the founders has founded another startup before. All regressions are estimated with a constant term, year of investment, startup company industry, startup company region, and startup company investment stage fixed effects (not reported). Robust standard errors clustered at the startup company level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
Founder: Top	0.00043***			
	(0.00010)			
Founder: Top US		0.00049***		
		(0.00010)		
Founder: Top European		0.00011		
		(0.00015)		
Investor: Top	-0.00065***			
	(0.00016)			
Investor: Top US		-0.00027*		
		(0.00014)		
Investor: Top European		-0.00043***		
		(0.00010)		
Both: Top			0.00051***	
			(0.00010)	
Both: Top US				0.00022**
				(0.00011)
Both: Top European				0.00146***
				(0.00022)
Distance	-0.00096***	-0.00096***	-0.00095***	-0.00095***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
VC Performance	0.00010	0.00021	0.00002	-0.00002
	(0.00060)	(0.00059)	(0.00060)	(0.00060)
VC Experience	-0.00021***	-0.00018***	-0.00026***	-0.00027***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Serial Founder	0.00038***	0.00037***	0.00038***	0.00039***
	(0.00013)	(0.00013)	(0.00013)	(0.00013)
Year Fixed Effect	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes
Region Fixed Effect	yes	yes	yes	yes
Stage Fixed Effect	yes	yes	yes	yes
Pseudo R^2	0.1319	0.1319	0.1318	0.1319
Observations	4,738,861	4,738,861	4,738,861	4,738,861

should be more likely that an investor affiliated with an Ivy League university invests in the startup of a founder who also attended a (different) Ivy League university.[16] In specification (3) this effect is analyzed in the broadest definition capturing founders and investor pairs that attended any of the top schools as defined in section 4.3.2. The effect of *Both: Top* is positive and of similar magnitude (0.051 percentage points) as the effect for the founder variables discussed above. However, when I split the variable in *Both: Top US* and *Both: Top European* in specification (4) the effect size differs strongly. The marginal effect of *Both: Top European* is almost 7 times higher than the one of *Both: Top US*.[17] If both founder and investor attended a top European university the likelihood of an investment increases by 0.146 percentage points, which corresponds to a substantial 16.4% increase over the baseline probability. In combination with the non-significant effect of *Founder: Top European*, this indicates that reciprocity is an important factor which is indicative evidence that alumni networks are behind this effect.

Educational Ties

After presenting the first indicative evidence for the value of alumni networks in the matching process between startups and VC firms, the regressions in table 4.6 shed more light on the effect of educational ties between founders and investors. If alumni networks are the driving factor behind the value of top-university affiliations, the marginal effect of a shared university affiliation between founder and investor reported in table 4.6 should be considerably higher than the effects presented in table 4.5.

Specifications (1) - (3) explore the effect of educational ties at different granularity levels. The results indicate that startups and VC firms are substantially more likely to match in the presence of an educational tie. All coefficients are highly statistically and economically significant. Specification (1) presents the general effect of educational ties irrespective of the tie stemming from a top or non-top university. When a founder and an investor attended the same university, the likelihood of an investment increases by 0.21 percentage points or 23.6% relative to the baseline probability of investment. This effect is almost 5 times higher than the one reported for *Founder: Top* and still over 4

[16] The Ivy League was originally a sports conference in which the member universities compete against each other. Similar inter-university networks are known in other countries, too. For example, in Europe, many private business schools regularly compete in the WHU Euromasters sports event. Thus, it makes sense to explore the potential effect of these inter-university alumni networks among top schools.

[17] In an unreported regression I repeat the analysis for a dummy that measures the same effect just for Ivy League universities. The effect of a shared Ivy League affiliation between founder and investor is around 5 times higher than the effect of *Both: Top US*. This shows that even within the group of elite universities in the U.S., not every university seems to offer the same alumni network benefits.

Table 4.6.: The Effect of a Shared Educational Background on Investment

This table reports marginal effects of probit regressions studying the effect of a shared educational background between founders and investors on the probability of a match between a startup and a VC firm. The sample comprises 4,738,861 observations, consisting of 42,101 factual and 4,696,760 counterfactual investments. The dependent variable is *match*, a dummy variable equal to one for actual investments, and equal to zero for counterfactual investments. *Both: Same, Same Top, Same non-Top, Same Top US, Same Top European* are dummy variables equal to one when at least one of the founders and anyone of the partners at the VC firm attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Distance* is the natural logarithm of the distance between startup and VC firm. *VC Performance* is the VC firm's IPO ratio up to the current deal. *VC Experience* is the natural logarithm of the number of investment rounds the VC firm has participated in up to the current deal. *Serial Founder* is a dummy variable equal to one when at least one of the founders has founded another startup before. All regressions are estimated with a constant term, year of investment, startup company industry, startup company region, and startup company investment stage fixed effects (not reported). Robust standard errors clustered at the startup company level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)
Both: Same	0.00210***		
	(0.00011)		
Both: Same Top		0.00185***	
		(0.00012)	
Both: Same non-Top		0.00371***	0.00364***
		(0.00026)	(0.00026)
Both: Same Top US			0.00151***
			(0.00013)
Both: Same Top European			0.00455***
			(0.00048)
Distance	-0.00092***	-0.00092***	-0.00092***
	(0.00002)	(0.00002)	(0.00002)
VC Performance	-0.00020	-0.00023	-0.00024
	(0.00060)	(0.00060)	(0.00060)
VC Experience	-0.00040***	-0.00041***	-0.00040***
	(0.00003)	(0.00003)	(0.00003)
Serial Founder	0.00028**	0.00030**	0.00031**
	(0.00013)	(0.00013)	(0.00013)
Year Fixed Effect	yes	yes	yes
Industry Fixed Effect	yes	yes	yes
Region Fixed Effect	yes	yes	yes
Stage Fixed Effect	yes	yes	yes
Pseudo R^2	0.1327	0.1328	0.1329
Observations	4,738,861	4,738,861	4,738,861

times as high as the effect of *Both: Top* in table 4.5. To get a better understanding of whether this effect is different for top universities and other universities, specifications (2) and (3) use finer classifications for the dummy variables. Specification (2) differentiates between top university ties and non-top university ties. Surprisingly, the effect observed for top universities (an increase of 0.185 percentage points) is only about half as strong as the one for non-top universities (an increase of 0.371 percentage points). If both founder and investor attended the same non-top university the investment likelihood increases by 41.7% over the baseline investment probability. Finally, in specification (3) the top-university effect is broken down into U.S. and European top universities. The effect of *Both: Top European* is about three times larger than the effect of *Both: Top US*, which means that investor-alumni of European top universities are much more likely to match with founders affiliated with their own alma mater than alumni-investors of top U.S. universities. Overall, the results largely confirm the value of educational ties for any type of university in venture capital deals. Considering that the size of the effect of non-top universities exceeds the top-university effect by a factor of three, the results do not seem to be driven solely by quality signals or the reputation of certain universities but at least to a substantial extent by the common alumni network of founders and investors.

Redundant and Exclusive Educational Ties

As discussed in section 4.3.2 only a few universities make up a substantial share of all investor and founder affiliations and about a third of all actual investments involve an educational tie. In fact, many investments even involve more than one educational tie between partners and founders. But do these redundant ties have the same value for the matching process as the 'first' tie? Further, it seems likely that for example a VC-firm partner affiliated with a university attended by many founders as well will be faced with several investment opportunities involving an educational tie.[18] Affiliations to other universities might lead to more exclusive educational ties, i.e. in the most exclusive case, only one of the potential investments would face an educational tie. Thus, as a logical next step, I explore the effect of redundant ties and scrutinize the role of exclusivity of ties in table 4.7.

[18] For example, many VC firms have their headquarters in Sand Hill Road near Stanford University. Considering that many of the partners at the firms attended Stanford themselves and Stanford produces a great number of founders it can be assumed that at any given point in time their deal flow includes various investment opportunities with an educational tie to one of the founders. It is logical to assume that in such cases the value of an educational tie for the investment decision is much less pronounced than on average.

Table 4.7.: The Effect of Redundant and Exclusive Educational Ties on Investment

This table reports marginal effects of probit regressions studying the effect of redundant educational ties between founders and investors and the effect of exclusive educational ties on the probability of a match between a startup and a VC firm. The sample comprises 4,738,861 observations, consisting of 42,101 factual and 4,696,760 counterfactual investments. The dependent variable is *match*, a dummy variable equal to one for actual investments, and equal to zero for counterfactual investments. *Both: Same, Same Top, Same non-Top* are dummy variables equal to one when at least one of the founders and anyone of the partners at the VC firm attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Both: Same, Same Top, Same non-Top (redundant)* are dummy variables equal to one when more than one founder and/or partner at the VC firm attended the same, the same top, the same non-top university, respectively, and zero otherwise. *Both: Same, Same Top, Same non-Top (scaled)* are scaled versions of the dummy variable that are constructed by dividing the respective dummy variable by the number of counterfactual investments that entail the same educational tie. *Distance* is the natural logarithm of the distance between startup and VC firm. *VC Performance* is the VC firm's IPO ratio up to the current deal. *VC Experience* is the natural logarithm of the number of investment rounds the VC firm has participated in up to the current deal. *Serial Founder* is a dummy variable equal to one when at least one of the founders has founded another startup before. All regressions are estimated with a constant term, year of investment, startup company industry, startup company region, and startup company investment stage fixed effects (not reported). Robust standard errors clustered at the startup company level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
Both: Same	0.00172***			
	(0.00015)			
Both: Same (redundant)	0.00059***			
	(0.00016)			
Both: Same Top		0.00141***		
		(0.00017)		
Both: Same Top (redundant)		0.00055***		
		(0.00019)		
Both: Same non-Top		0.00292***		
		(0.00026)		
Both: Same non-Top (redundant)		0.00207***		
		(0.00034)		
Both: Same (scaled)			0.03247***	
			(0.00053)	
Both: Same Top (scaled)				0.03005***
				(0.00061)
Both: Same non-Top (scaled)				0.01890***
				(0.00050)
Distance	-0.00092***	-0.00092***	-0.00093***	-0.00093***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
VC Performance	-0.00022	-0.00025	0.00000	-0.00007
	(0.00060)	(0.00060)	(0.00059)	(0.00059)
VC Experience	-0.00042***	-0.00043***	-0.00026***	-0.00030***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Serial Founder	0.00027**	0.00030**	0.00030**	0.00030**
	(0.00013)	(0.00013)	(0.00013)	(0.00013)
Year Fixed Effect	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes
Region Fixed Effect	yes	yes	yes	yes
Stage Fixed Effect	yes	yes	yes	yes
Pseudo R^2	0.1327	0.1330	0.1445	0.1438
Observations	4,738,861	4,738,861	4,738,861	4,738,861

Specifications (1) and (2) extend the basic analysis with additional dummies that indicate if there is more than one educational tie.[19] In specification (1) *Both: Same (redundant)* is included to measure the overall effect of additional educational ties. The results show that additional ties increase the likelihood of an investment to a lesser extent than the 'first' tie. While the marginal effect is highly statistically significant, it is only about one-third the size of the main effect of *Both: Same* (a 0.059 percentage points increase vs. a 0.172 percentage points increase). Still, the fact that redundant ties increase the likelihood of investment indicates that educational ties do not simply help investors to increase deal flow or identify potential investments by decreasing search cost (see e.g. Podolny 1994; Kuhnen 2009). This hypothesis is in line with Fuchs et al. (2021) who find the same result for redundant educational ties between target firm CEOs and fund managers in the context of winning a PE deal. They argue that redundant ties are more important in competitive environments than in non-competitive environments. One explanation is that educational ties in the entrepreneurial finance environment might influence the interaction and relationship of founders and investors through better information flow and reduced moral hazard based on shared beliefs and suppositions formed at universities or interpersonal trust (see e.g. Corwin and Schultz 2005; Colombo et al. 2022) created by belonging to the same peer group. Additionally, in specification (2) I explore if there is a difference in redundant ties between top and non-top universities. The general observation of a positive, but smaller effect holds for both cases. However, it is interesting to point out that the diminishing effect of redundant educational ties is smaller in the case of non-top universities. The marginal effect of a redundant tie is less than a third smaller than the effect of the 'first' tie. This is further evidence, that alumni networks do matter in the matching process for all types of universities and might even play a bigger role for non-top university attendants. In the VC context, it is important to point out, however, that non-top educational ties are much rarer (see table 4.3), which might partially explain the larger effect associated with non-top university ties.

To further analyze what role the exclusivity of educational ties plays, specifications (3) and (4) introduce a scaled variant of the *Both: Same* variable. To construct *Both: Same (scaled)*, the indicator variable *Both: Same* is divided by the number of counterfactual investments in its cohort that also involve the same type of educational tie. This basically transforms the variable into a quasi probability, because the resulting values are in an interval ranging from zero to one, with the value of one representing the most exclusive

[19] The dummies do not differentiate between redundant ties that stem from only three individuals (e.g. one founder sharing a university affiliation with two investment partners) and redundant ties that involve at least four individuals (e.g. two unique founder-investor pairs each sharing a university affiliation).

educational tie. The reported results confirm that the likelihood of investment increases the more exclusive an educational tie is. The marginal effects are positive and highly statistically significant in both specifications. In contrast to the results discussed so far, in specification (4) after accounting for the exclusivity of an educational tie the effect of non-top university ties is about one-third smaller than the effect of top university ties. This means that at the same level of exclusivity top-university affiliations do play a more important role than non-top affiliations. This can be interpreted as sign that alumni networks of top universities are more valuable in the VC matching process when they are a differentiating factor between investment opportunities.

Robustness Checks

I conduct several robustness checks to ensure that the results are unaffected by alternative model specifications and methodologies. A benefit of the large sample size and the counterfactual approach is the possibility to control for unobservable startup characteristics such as their quality and unobservable investor characteristics such as their ability or preferences. To rule out that the results suffer from an omitted variable bias, specifications (1) to (4) in table 4.8 introduce investor and startup fixed effects controlling for all time-invariant characteristics of the startups and VC firms. Due to the inclusion of the granular fixed effects *VC Experience* and *VC Performance* are not included in specifications (1) and (2), *Serial Founder* is not included in specifications (3) and (4), and some singleton observations are dropped in specifications (1) to (4). The results confirm that the main results reported so far are not altered by the inclusion of investor and startup fixed effects. All reported coefficients have the same sign and are quantitatively very similar to the main results.

Table 4.8.: Robustness Checks for the effect of Shared Educational Background on Investment

This table reports the results of several robustness checks studying the effect of a shared educational background between founders and investors on the probability of a match between a startup and a VC firm. Models (1) to (4) report coefficients of linear probability models using the full sample of up to 4,738,861 observations, consisting of 42,101 factual and 4,696,760 counterfactual investments. Some observations are dropped due to the inclusion of investor or startup fixed effects. Models (5) - (10) report marginal effects of probit regressions. The sample in models (5) and (6) only includes investments by U.S. VC firms, while the sample in models (7) and (8) only includes investments by European VC firms. The sample only includes one counterfactual per actual investment in models (9) and (10). The dependent variable is *match*, a dummy variable equal to one for actual investments, and equal to zero for counterfactual investments. *Both: Same, Same Top, Same non-Top* are dummy variables equal to one when at least one of the founders and anyone of the partners at the VC firm attended the same, the same top, or the same non-top university, respectively, and zero otherwise. *Distance* is the natural logarithm of the distance between startup and VC firm. *VC Performance* is the VC firm's IPO ratio up to the current deal. *VC Experience* is the natural logarithm of the number of investment rounds the VC firm has participated in up to the current deal. *Serial Founder* is a dummy variable equal to one when at least one of the founders has founded another startup before. All regressions are estimated with a constant term, and include fixed effects as indicated (not reported). Robust standard errors clustered at the startup company level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	Investor FE		Startup FE		U.S. sub-sample		Europe sub-sample		One Counterfactual	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Both: Same	0.00239***		0.00253***		0.00181***		0.00822***		0.04560***	
	(0.00014)		(0.00014)		(0.00011)		(0.00077)		(0.00386)	
Both: Same Top		0.00204***		0.00212***		0.00155***		0.00777***		0.04409***
		(0.00015)		(0.00016)		(0.00012)		(0.00085)		(0.00413)
Both: Same non-Top		0.00408***		0.00354***		0.00345***		0.01115***		0.05139***
		(0.00025)		(0.00025)		(0.00025)		(0.00177)		(0.00716)
Distance	-0.00132***	-0.00133***	-0.00124***	-0.00125***	-0.00101***	-0.00102***	-0.00070***	-0.00070***	-0.02723***	-0.02723***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00002)	(0.00002)	(0.00014)	(0.00014)	(0.00067)	(0.00067)
VC Performance			0.00119*	0.00118*	-0.00115*	-0.00119**	0.00631*	0.00633*	-0.01324	-0.01335
			(0.00068)	(0.00068)	(0.00060)	(0.00060)	(0.00340)	(0.00339)	(0.02168)	(0.02168)
VC Experience			-0.00049***	-0.00049***	-0.00039***	-0.00039***	-0.00033*	-0.00033*	-0.00304***	-0.00303***
			(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00018)	(0.00018)	(0.00107)	(0.00107)
Serial Founder	0.00005	0.00008			0.00037***	0.00040***	-0.00210***	-0.00207***	0.01882***	0.01897***
	(0.00017)	(0.00017)			(0.00013)	(0.00013)	(0.00075)	(0.00075)	(0.00452)	(0.00452)
Year Fixed Effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	no	no	yes	yes	yes	yes	yes	yes
Region Fixed Effect	yes	yes	no	no	yes	yes	yes	yes	yes	yes
Stage Fixed Effect	yes	yes	no	no	yes	yes	yes	yes	yes	yes
Investor Fixed Effect	yes	yes	no	no	no	no	no	no	no	no
Startup Fixed Effect	no	no	yes	yes	no	no	no	no	no	no
R^2	0.0319	0.0319	0.0641	0.0641	0.1118	0.1120	0.1868	0.1868	0.0785	0.0785
Observations	4,738,840	4,738,840	4,738,476	4,738,476	4,375,925	4,375,925	362,936	362,936	83,311	83,311
Type	OLS	OLS	OLS	OLS	Probit	Probit	Probit	Probit	Probit	Probit

To see if the results also hold in sub-samples, I split the sample based on the VC firms' locations. The sub-sample in models (5) and (6) only includes investments by U.S. VC firms, while the sub-sample in models (7) and (8) only includes investments by European VC firms. Due to the different number of observations of the two sub-samples the coefficients cannot be compared directly. However, the pattern within each sub-sample is consistent with the main results and across the two sub-samples. Educational ties increase the likelihood of an investment in the U.S. investor sub-sample as well as in the European investor sub-sample. In both sub-samples, the effect of top-university ties is smaller than the effect of non-top university ties.

Finally, specifications (9) and (10) limit the number of counterfactuals per actual investment to a one-for-one random draw to rule out that the high variance in the number of counterfactual investments per actual investment affects the results. The single counterfactual per actual investment is randomly drawn from the full cohort of counterfactuals that is included in the main sample. The results are consistent with the main analysis both qualitatively and quantitatively. Because of the much smaller fraction of counterfactuals in the sample, the 4.56 percentage point increase in the investment likelihood attributable to *Both: Same* corresponds to a relative increase of the baseline probability of about 11%.

4.4.2 Scope of the Funding Relationship

The analysis so far only concerned the likelihood of investment conditional on an educational tie. After having established the general importance of alumni networks in venture capital for the matching between founders and investors, the next logical step is to scrutinize whether a shared university affiliation also influences the nature of the funding relationship itself. In this part of the analysis, I test whether the scope of investment differs for deals involving educational ties. Specifically, I first test whether investors are more likely to act as lead investors or to take a board seat. Additionally and second, I analyze whether investors stick with a startup for more funding rounds. The regressions in tables 4.9, 4.10, and 4.11 are specified analog to equation 4.6:

$$\left.\begin{aligned} &\mathit{Lead\ Investor}_{i,j} \\ &\mathit{Board\ Seat}_{i,j} \\ &\mathit{Number\ of\ Rounds}_{i,j} \end{aligned}\right\} \begin{aligned} &= \alpha + \beta \mathit{Education}_{i,j} + \gamma \mathit{Controls}_{i,j} \\ &\quad + \delta \mathit{FE}(\mathit{Year}_{i,j},\ \mathit{Industry}_i,\ \mathit{Region}_i,\ \mathit{Stage}_i) \end{aligned} \tag{4.7}$$

However, in contrast to equation 4.6, in equation 4.7 *Lead Investor*, *Board Seat* or *Number of Rounds* serve as dependent variable and the sample only includes the 42,101 actual investments. I rely on probit regressions for the former two dependent variables and poisson regressions for the latter variable. Table 4.9 reports marginal effects of the probit regressions exploring whether investors are more likely to lead an investment syndicate for a startup from their alumni network. The lead investor plays a very important role because the lead investor usually initiates the funding round and actively looks for other potential investors. Specifications (1) to (3) rely on the broad definition of an educational tie involving any partner at the VC firm. The results are ambiguous. Only the positive effect for non-top universities is statistically significant at the 1% level, while the general effect is statistically significant only at the 10% level and *Both: Same Top* is not significant at all. However, this non-significance is only attributable to top U.S. university ties, while *Both: Same Top European* shows a significant positive effect. A potential reason for the ambiguous results could be that the broad definition of educational ties, might underestimate the effect of a shared university affiliation. The methodology likely finds too many alumni network connections because it takes into account all partners at the VC firm to identify educational ties. This will inevitably also include ties with partners at the VC firm that had nothing to do with the investment and thus might have had no interaction with the founders at all. As this step of the analysis only includes actual investments, information on investment partners can be exploited to ensure only individuals actually involved in a specific investment are considered to identify educational ties. Thus, in specifications (4) to (6), I include the narrower definitions of educational ties introduced in section 4.3.2. A narrow educational tie is only counted if the investment partner supervising the investment has a shared university affiliation with at least one of the founders. The results across specifications (4) to (6) show consistent positive, statistically and economically significant effects of similar magnitude for all granularity levels. For example, the likelihood of acting as lead investor increases by 14.4 percentage points in specification (4), which corresponds to a relative increase of about 37% compared to the unconditional probability. The effect of non-top universities is even higher (a 45% relative increase), again confirming that school quality is not the decisive factor behind the effect of educational ties. Moreover, the positive relationship between acting as lead investor and an educational tie does not differ significantly between top U.S. and top European universities.

Another important role an investor can take over is a board seat. Board seats are the most direct way for an investor to actively shape or take critical decisions for the startup. This means giving an investor a board seat transfers substantial influence over the company to the investor, which requires a high level of trust between the parties. In table 4.10 I present results on the analysis of whether investors are more likely to

Table 4.9.: Scope: The Effect of a Shared Educational Background on Acting as Lead Investor

This table reports marginal effects of probit regressions studying the effect of shared educational background between founders and investors on the probability of acting as the lead investor. The sample comprises 42,101 factual investments. The dependent variable is *lead investor*, a dummy variable equal to one when the VC firm acts as the lead investor in the funding round. *Both: Same, Same Top, Same non-Top, Same Top US, Same Top European* are dummy variables equal to one when at least one of the founders and anyone of the partners at the VC firm attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Both: Same, Same Top, Same non-Top, SameTop US, Same Top European (narrow)* are dummy variables equal to one when at least one of the founders and the deal's investment partner attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Distance* is the natural logarithm of the distance between startup and VC firm. *VC Performance* is the VC firm's IPO ratio up to the current deal. *VC Experience* is the natural logarithm of the number of investment rounds the VC firm has participated in up to the current deal. *Serial Founder* is a dummy variable equal to one when at least one of the founders has founded another startup before. All regressions are estimated with a constant term, year of investment, startup company industry, startup company region, and startup company investment stage fixed effects (not reported). Robust standard errors clustered at the startup company level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Both: Same	0.010*					
	(0.005)					
Both: Same Top		0.004				
		(0.006)				
Both: Same non-Top		0.036***	0.035***			
		(0.010)	(0.010)			
Both: Same Top US			-0.001			
			(0.006)			
Both: Same Top European			0.028**			
			(0.013)			
Both: Same (narrow)				0.144***		
				(0.009)		
Both: Same Top (narrow)					0.137***	
					(0.010)	
Both: Same non-Top (narrow)					0.176***	0.175***
					(0.023)	(0.023)
Both: Same Top US (narrow)						0.135***
						(0.011)
Both: Same Top European (narrow)						0.147***
						(0.029)
Distance	-0.001	-0.001	-0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
VC Performance	0.026	0.026	0.026	0.028	0.028	0.028
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
VC Experience	0.048***	0.048***	0.048***	0.047***	0.047***	0.047***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Serial Founder	-0.053***	-0.053***	-0.052***	-0.056***	-0.056***	-0.056***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Year Fixed Effect	yes	yes	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes	yes	yes
Region Fixed Effect	yes	yes	yes	yes	yes	yes
Stage Fixed Effect	yes	yes	yes	yes	yes	yes
Pseudo R^2	0.0643	0.0645	0.0646	0.0686	0.0687	0.0686
Observations	42,101	42,101	42,101	42,101	42,101	42,101

Table 4.10.: The Effect of a Shared Educational Background on Taking a Board Seat

This table reports marginal effects of probit regressions studying the effect of shared educational background between founders and investors on the probability of the investor taking a board seat. The sample comprises 42,101 factual investments. The dependent variable is *board seat*, a dummy variable equal to one when the VC firm took a board seat after the investment, and zero otherwise. *Both: Same, Same Top, Same non-Top, Same Top US, Same Top European* are dummy variables equal to one when at least one of the founders and anyone of the partners at the VC firm attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Both: Same, Same Top, Same non-Top, SameTop US, Same Top European (narrow)* are dummy variables equal to one when at least one of the founders and the deal's investment partner attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Distance* is the natural logarithm of the distance between startup and VC firm. *VC Performance* is the VC firm's IPO ratio up to the current deal. *VC Experience* is the natural logarithm of the number of investment rounds the VC firm has participated in up to the current deal. *Serial Founder* is a dummy variable equal to one when at least one of the founders has founded another startup before. All regressions are estimated with a constant term, year of investment, startup company industry, startup company region, and startup company investment stage fixed effects (not reported). Robust standard errors clustered at the startup company level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Both: Same	0.019***					
	(0.005)					
Both: Same Top		0.015***				
		(0.005)				
Both: Same non-Top		0.036***	0.033***			
		(0.009)	(0.009)			
Both: Same Top US			0.001			
			(0.005)			
Both: Same Top European			0.058***			
			(0.012)			
Both: Same (narrow)				0.333***		
				(0.009)		
Both: Same Top (narrow)					0.321***	
					(0.010)	
Both: Same non-Top (narrow)					0.381***	0.380***
					(0.021)	(0.021)
Both: Same Top US (narrow)						0.308***
						(0.011)
Both: Same Top European (narrow)						0.357***
						(0.026)
Distance	-0.002**	-0.002**	-0.002**	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
VC Performance	0.002	0.001	0.002	0.008	0.008	0.009
	(0.026)	(0.026)	(0.026)	(0.025)	(0.025)	(0.025)
VC Experience	0.040***	0.040***	0.040***	0.037***	0.038***	0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Serial Founder	-0.006	-0.006	-0.005	-0.014**	-0.014**	-0.014**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Year Fixed Effect	yes	yes	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes	yes	yes
Region Fixed Effect	yes	yes	yes	yes	yes	yes
Stage Fixed Effect	yes	yes	yes	yes	yes	yes
Pseudo R^2	0.1128	0.1129	0.1132	0.1412	0.1414	0.1403
Observations	42,101	42,101	42,101	42,101	42,101	42,101

take over a board seat in the presence of educational ties. The structure of the table is as above: Specifications (1) to (3) employ the broad education tie definition, while specifications (4) to (6) repeat the same analysis with the narrow definition. As observed before, the effects of the broad definitions are much smaller than the effect of the narrow definition. Specification (1) reports a 1.9 percentage points increased likelihood of taking a board seat, while specification (4) shows a 33.3 percentage points increase. The effect of the narrow definition translates to a relative increase of 115%, i.e. more than double the unconditional probability. Effects of this magnitude can be observed for top and non-top university ties, as well as for top European and top U.S. ties. An increase of this magnitude is clearly of economical significance and shows that alumni networks lead to deeper business relationships among alumni in the venture capital context.

Finally, I explore how long an investor keeps actively investing in a specific startup in terms of the number of funding rounds the investor participates in over the startup's full funding history in table 4.11. The results consistently show a positive relationship between the number of funding rounds and educational ties, which suggests that investors stay involved longer in investments involving educational ties. In an unreported comparison of group means, the average number of funding rounds not involving a narrow educational tie (1.7) is about 0.5 smaller than the average number of funding rounds involving a tie (2.2). The multivariate analysis shows an effect of similar magnitude. The effects in specifications (4) to (6) indicate that depending on the type of educational tie, investors participate in 0.266 to 0.331 more funding rounds per startup. The results suggest that investors also invest higher amounts in startups with educational ties, because typically funding amounts increase with each funding round. However, due to to only partially available information about funding amounts in my dataset, I cannot test this hypothesis in the sample. Still, the results confirm the earlier findings and show that educational ties not only increase the likelihood of investment but also expand the scope of the investment relationship.

4.4.3 Riskiness of the Investment

Next, I examine whether educational ties are related to investors being willing to take on more risky investments. Investing in earlier funding rounds or younger startups is considered riskier than investing in later rounds or more mature companies due to the higher level of information asymmetry and the higher potential of the startup to fail (Koenig and Burghof 2022; Cochrane 2005). In line with this fact, Bottazzi et al. (2016) show that a higher level of trust is positively related to the likelihood of investing in earlier funding rounds. If educational ties do not only serve as a channel for the

Table 4.11.: Scope: The Effect of a Shared Educational Background on the Number of Rounds

This table reports marginal effects of poisson regressions studying the effect of shared educational background between founders and investors on the number of investment rounds the VC firm participates in. The sample comprises 42,101 factual investments. The dependent variable is *number of rounds*, the number of the startup's investment rounds the VC firm participated in. *Both: Same, Same Top, Same non-Top, Same Top US, Same Top European* are dummy variables equal to one when at least one of the founders and anyone of the partners at the VC firm attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Both: Same, Same Top, Same non-Top, SameTop US, Same Top European (narrow)* are dummy variables equal to one when at least one of the founders and the deal's investment partner attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Distance* is the natural logarithm of the distance between startup and VC firm. *VC Performance* is the VC firm's IPO ratio up to the current deal. *VC Experience* is the natural logarithm of the number of investment rounds the VC firm has participated in up to the current deal. *Serial Founder* is a dummy variable equal to one when at least one of the founders has founded another startup before. All regressions are estimated with a constant term, year of investment, startup company industry, startup company region, and startup company investment stage fixed effects (not reported). Robust standard errors clustered at the startup company level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Both: Same	0.070***					
	(0.013)					
Both: Same Top		0.064***				
		(0.015)				
Both: Same non-Top		0.097***	0.092***			
		(0.023)	(0.023)			
Both: Same Top US			0.048***			
			(0.016)			
Both: Same Top European			0.094***			
			(0.031)			
Both: Same (narrow)				0.324***		
				(0.024)		
Both: Same Top (narrow)					0.325***	
					(0.026)	
Both: Same non-Top (narrow)					0.331***	0.329***
					(0.052)	(0.052)
Both: Same Top US (narrow)						0.313***
						(0.029)
Both: Same Top European (narrow)						0.266***
						(0.066)
Distance	-0.010***	-0.010***	-0.010***	-0.009***	-0.009***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
VC Performance	0.021	0.021	0.021	0.035	0.035	0.036
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)
VC Experience	0.086***	0.086***	0.087***	0.088***	0.088***	0.088***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Serial Founder	0.028	0.029	0.029	0.023	0.023	0.024
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Year Fixed Effect	yes	yes	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes	yes	yes
Region Fixed Effect	yes	yes	yes	yes	yes	yes
Stage Fixed Effect	yes	yes	yes	yes	yes	yes
Pseudo R^2	0.0375	0.0375	0.0375	0.0386	0.0386	0.0385
Observations	42,101	42,101	42,101	42,101	42,101	42,101

identification of potential investments but also lead to a higher level of generalized trust between the founder and investor, educational ties should also be related to an increased likelihood of investing in the first funding round of a startup or investing in younger startups. I empirically explore these relationships using equation 4.8.

$$\left.\begin{array}{l} \mathit{First\ Round}_{i,j} \\ \mathit{Age\ of\ Startup}_{i,j} \end{array}\right\} \begin{array}{l} = \alpha + \beta \mathit{Education}_{i,j} + \gamma \mathit{Controls}_{i,j} \\ \quad + \delta \mathit{FE(Year}_{i,j},\ \mathit{Industry}_i,\ \mathit{Region}_i,\ \mathit{Stage}_i) \end{array} \tag{4.8}$$

Table 4.12 reports the results of probit regressions analyzing whether the VC firm invested in the first funding round of a startup. All statistically significant controls show the expected signs. *VC Performance* does not statistically significant relate to investing in a first round. *Distance* is negatively related to investing in a first round, while more experienced VCs are more likely to invest in a first round. Serial founders are also more likely to attract investors to invest in their startup's first round.

Specifications (1) to (3) include the indicator variables for educational ties that take into account the whole partner team to identify educational ties. Overall, the results show that educational ties of any kind are related to a higher likelihood of an investor joining the first funding round of a startup. For example, according to specification (1), if a founder and investor share a university affiliation the likelihood of investing in the first funding round is 2.3 percentage points higher. This corresponds to a relative increase of roughly 6% over the unconditional baseline probability of investing in a first round in the sample. Further, consistent with the analysis of the matching likelihood, the effect size for non-top universities is almost double the effect size of top universities.

The results for the narrow educational ties definition in specifications (4) to (6) are qualitatively the same as for the broader definition. However, the effect size is significantly higher. For example, non-top university ties are associated with a 2.5 times higher effect when comparing specifications (2) and (5). Specifically, an educational tie stemming from a non-top university between the investment partner and a founder is associated with a 24% increased likelihood of investing in the first funding round, while the effect of *Both: Same non-Top* is a relative increase of 9.9% only. The results strongly support the notion, that the positive effect of educational ties is driven by the increased generalized trust of investors and founders belonging to the same alumni network.

To further corroborate the finding that educational ties lead to a higher level of generalized trust, table 4.13 reports results of linear regressions studying the relationship of a shared educational background between founders and investors and the age of a startup at the time of investment. The general specification of the regressions is as before, however, the dependent variable *Age of Startup* is now continuous. Startup age serves as an

Table 4.12.: Timing: The Effect of a Shared Educational Background on Investing in the First Round

This table reports marginal effects of probit regressions studying the effect of shared educational background between founders and investors on the probability of investing in the startup's first investment round. The sample comprises 42,101 factual investments. The dependent variable is *first round*, a dummy variable equal to one when the VC firm invested in the startup's first funding round, and zero otherwise. *Both: Same, Same Top, Same non-Top, Same Top US, Same Top European* are dummy variables equal to one when at least one of the founders and anyone of the partners at the VC firm attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Both: Same, Same Top, Same non-Top, SameTop US, Same Top European (narrow)* are dummy variables equal to one when at least one of the founders and the deal's investment partner attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Distance* is the natural logarithm of the distance between startup and VC firm. *VC Performance* is the VC firm's IPO ratio up to the current deal. *VC Experience* is the natural logarithm of the number of investment rounds the VC firm has participated in up to the current deal. *Serial Founder* is a dummy variable equal to one when at least one of the founders has founded another startup before. All regressions are estimated with a constant term, year of investment, startup company industry, startup company region, and startup company investment stage fixed effects (not reported). Robust standard errors clustered at the startup company level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Both: Same	0.023***					
	(0.005)					
Both: Same Top		0.020***				
		(0.006)				
Both: Same non-Top		0.038***	0.037***			
		(0.009)	(0.009)			
Both: Same Top US			0.016**			
			(0.007)			
Both: Same Top European			0.024*			
			(0.013)			
Both: Same (narrow)				0.035***		
				(0.009)		
Both: Same Top (narrow)					0.025**	
					(0.010)	
Both: Same non-Top (narrow)					0.092***	0.092***
					(0.020)	(0.020)
Both: Same Top US (narrow)						0.012
						(0.011)
Both: Same Top European (narrow)						0.073***
						(0.026)
Distance	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
VC Performance	0.030	0.030	0.030	0.035	0.035	0.035
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
VC Experience	0.008***	0.008***	0.008***	0.009***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Serial Founder	0.064***	0.064***	0.065***	0.065***	0.065***	0.065***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Year Fixed Effect	yes	yes	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes	yes	yes
Region Fixed Effect	yes	yes	yes	yes	yes	yes
Stage Fixed Effect	yes	yes	yes	yes	yes	yes
Pseudo R^2	0.1819	0.1820	0.1819	0.1818	0.1819	0.1820
Observations	42,101	42,101	42,101	42,101	42,101	42,101

alternative proxy for investment risk. Information asymmetry is can be considered higher for younger companies, because of the issue of hidden information (Jensen and Meckling 1976) and the fact that much of a company's quality might not have been revealed, yet. Following the argument for investing in first rounds, it should be expected that educational ties are related to investing in younger startups.

The results in specifications (1) - (6) largely match the results discussed above for investing in the first funding round and confirm that in presence of educational ties VC firms invest in younger startups. The coefficients are consistently negative in all specifications. While the effect size is of similar magnitude across all specifications involving the narrow definitions of educational ties, the point estimate is larger for top universities in specifications (2) and (3) compared to non-top universities.

4.4.4 Investment Success

In this final step of the analysis, I explore whether investments involving educational ties perform better or worse than other investments. As there is no detailed cashflow data available in the sample, well-performing investments are proxied via the investment's exit channel. IPOs are considered the most lucrative exit channel because they usually create the highest returns for investors. Relying on IPOs as a proxy for investment performance is a common approach in the literature (e.g. Gompers and Lerner 2000b; Bottazzi et al. 2008; Nahata 2008; Y. Li et al. 2014; Bengtsson and David H. Hsu 2015). The sample in this section is limited to investments before 2017 to ensure enough time to observe an exit for all included investments. It comprises 27,014 factual investments. The unconditional probability of exiting via IPO in the sample is 5.6%. In equation 4.9, the dependent variable *Success* is a dummy variable equal to one when the investment eventually exited via an IPO.

$$\begin{aligned} Success_{i,j} = \alpha + \beta Education_{i,j} + \gamma Controls_{i,j} \\ + \delta FE(Year_{i,j},\ Industry_i,\ Region_i,\ Stage_i,\ Investor_j) \end{aligned} \tag{4.9}$$

Besides the controls and fixed effects included before, one additional performance-related control variable is included in all specifications. *Syndicate size* controls for the effect that syndicated deals and larger syndicates perform better than other investments (Tykvová and Schertler 2014; Tian 2012; Das et al. 2011). Further, in specifications (7) and (8) I include investor fixed effects controlling for all time-invariant investor characteristics. 513 observations are dropped in these specifications because otherwise some investors only appear in the sample once leading to singleton investor groups for the fixed effects.

Table 4.13.: Timing: The Relationship between Shared Educational Background and Startup Age

This table reports the results of OLS regressions studying the relationship of shared educational background between founders and investors and the age of a startup at the time of investment. The sample comprises 42,101 factual investments. The dependent variable is *age of startup*, the natural logarithm of the startup's age in years at the time of investment. *Both: Same, Same Top, Same non-Top, Same Top US, Same Top European* are dummy variables equal to one when at least one of the founders and anyone of the partners at the VC firm attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Both: Same, Same Top, Same non-Top, SameTop US, Same Top European (narrow)* are dummy variables equal to one when at least one of the founders and the deal's investment partner attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Distance* is the natural logarithm of the distance between startup and VC firm. *VC Performance* is the VC firm's IPO ratio up to the current deal. *VC Experience* is the natural logarithm of the number of investment rounds the VC firm has participated in up to the current deal. *Serial Founder* is a dummy variable equal to one when at least one of the founders has founded another startup before. All regressions are estimated with a constant term, year of investment, startup company industry, startup company region, and startup company investment stage fixed effects (not reported). Robust standard errors clustered at the startup company level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Both: Same	-0.072***					
	(0.007)					
Both: Same Top		-0.083***				
		(0.008)				
Both: Same non-Top		-0.029***	-0.028***			
		(0.011)	(0.011)			
Both: Same Top US			-0.086***			
			(0.008)			
Both: Same Top European			-0.044***			
			(0.015)			
Both: Same (narrow)				-0.059***		
				(0.010)		
Both: Same Top (narrow)					-0.059***	
					(0.011)	
Both: Same non-Top (narrow)					-0.055**	-0.055**
					(0.025)	(0.025)
Both: Same Top US (narrow)						-0.057***
						(0.012)
Both: Same Top European (narrow)						-0.057**
						(0.029)
Distance	0.009***	0.009***	0.009***	0.010***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
VC Performance	-0.016	-0.017	-0.017	-0.028	-0.028	-0.028
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
VC Experience	-0.017***	-0.017***	-0.017***	-0.022***	-0.022***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Serial Founder	-0.214***	-0.214***	-0.214***	-0.219***	-0.219***	-0.219***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Year Fixed Effect	yes	yes	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes	yes	yes
Region Fixed Effect	yes	yes	yes	yes	yes	yes
Stage Fixed Effect	yes	yes	yes	yes	yes	yes
Adj. R^2	0.3581	0.3585	0.3585	0.3558	0.3558	0.3558
Observations	42,101	42,101	42,101	42,101	42,101	42,101

Table 4.14.: Success: The Relationship between Educational Background and Exit Outcome

This table reports the results of regressions studying the relationship between the educational background of founders and investors and the exit outcome. Models (1) to (6) report marginal effects of probit models. Models (7) and (8) report coefficients of linear probability models. The sample is limited to investments before 2017 to ensure enough time to observe an exit. It comprises 27,014 factual investments. In specifications (7) and (8), 513 singleton observations are dropped due to the inclusion of investor fixed effects. The dependent variable is *Success*, a dummy equal to one for investments that eventually were exited via IPO. *Founder: Top* is a dummy variable equal to one when at least one of the founders attended any top university, and zero otherwise. *Investor: Top* is a dummy variable equal to one when at least one of the partners at the VC firm attended any top university, and zero otherwise. *Both: Top* is a dummy variable equal to one when at least one of the founders and anyone of the partners at the VC firm attended any top university, and zero otherwise.*Both: Same, Same Top, Same non-Top* are dummy variables equal to one when at least one of the founders and anyone of the partners at the VC firm attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Both: Same, Same Top, Same non-Top (narrow)* are dummy variables equal to one when at least one of the founders and the deal's investment partner attended the same, the same top, the same non-top, the same top US, or the same top European university, respectively, and zero otherwise. *Distance* is the natural logarithm of the distance between startup and VC firm. *VC Performance* is the VC firm's IPO ratio up to the current deal. *VC Experience* is the natural logarithm of the number of investment rounds the VC firm has participated in up to the current deal. *Serial Founder* is a dummy variable equal to one when at least one of the founders has founded another startup before. *Syndicate Size* is the number of investors participating in the funding round. All regressions are estimated with a constant term, and include fixed effects as indicated (not reported). Robust standard errors clustered at the startup company level are reported in parentheses. *, **, *** refer to significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Founder: Top	0.006							
	(0.006)							
Investor: Top	0.005							
	(0.005)							
Both: Top		0.007						
		(0.005)						
Both: Same			0.010**					
			(0.004)					
Both: Same Top				0.010*				
				(0.005)				
Both: Same non-Top				0.010				
				(0.007)				
Both: Same (narrow)					0.023***		0.024***	
					(0.006)		(0.008)	
Both: Same Top (narrow)						0.022***		0.022***
						(0.007)		(0.009)
Both: Same non-Top (narrow)						0.033**		0.036**
						(0.015)		(0.016)
Distance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
VC Performance	0.089***	0.089***	0.089***	0.089***	0.090***	0.090***		
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)		
VC Experience	0.001	0.001	0.001	0.001	0.001	0.001		
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		
Serial Founder	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***	0.023**	0.023**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Syndicate Size	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year Fixed Effect	yes	yes	yes	yes	yes	yes	yes	yes
Industry Fixed Effect	yes	yes	yes	yes	yes	yes	yes	yes
Region Fixed Effect	yes	yes	yes	yes	yes	yes	yes	yes
Stage Fixed Effect	yes	yes	yes	yes	yes	yes	yes	yes
Investor Fixed Effect	no	no	no	no	no	no	yes	yes
Pseudo/Adj. R^2	0.1942	0.1942	0.1946	0.1946	0.1955	0.1956	0.1220	0.1220
Observations	27,014	27,014	27,014	27,014	27,014	27,014	26,501	26,501

Table 4.14 reports marginal effects of probit regressions and results of linear probability models exploring the relationship of educational background and exit success. As expected, the results show a positive sign for past *VC performance*, which is in line with the literature on performance persistence in entrepreneurial finance (Nanda et al. 2020). The same effect is observable for serial founders, which is also attributable to the performance persistence of serial startup founders (Gompers et al. 2010). Larger syndicates are also related to a higher likelihood of an IPO exit. *VC experience* and *distance* have no significant effect.

Specification (1) includes individual top university affiliations of founders and investors. The coefficients are not statistically significant, which means that founders or investors from top universities are not more successful in terms of exit success. This is in line with the findings so far that confirm that university quality is not the driving factor behind the results. Specification (2) substantiates this observation. Even if both investor and founder went to a top university no statistically significant effect on a successful investment outcome can be observed. However, the results in specifications (3) to (6) show a statistically significant positive relationship between educational ties and investment success. The coefficients of the narrow definitions of educational ties are two to three times larger than those of the broader definitions. For example, the reported marginal effect of *Both: Same (narrow)* in specification (5) means that an educational tie is associated with a 2.3 percentage points increased likelihood of an IPO exit. Given the low unconditional baseline probability of an IPO, this increase corresponds to a 41% boost in the likelihood of exiting via IPO. Thus, the results are not only statistically significant but also highly economically relevant. The effect can be observed for all types of educational ties and is even stronger for non-top university ties. Specifications (7) and (8) show that the results hold even when investor fixed effects are included in the model. Overall the results indicate that educational ties are related to better investment outcomes. This strongly suggests that educational ties reduce information asymmetries and improve collaboration between founders and investors. Combined with the results on the relationship between educational ties and risk-taking and investment scope, the results strongly suggest that relying on alumni networks for deal sourcing is rational behavior leading to more successful venture capital funding relationships for all parties involved.

4.4.5 Limitations

Even though the results in this paper are robust to diverse variations in model specification and several robustness checks they are not without limitations. First, the sample itself might be biased due to data availability. For an investment to be included in the sample, the educational backgrounds of at least one founder and at least one VC partner have to be available. This requirement in theory might skew the sample to include a higher share of investments involving individuals affiliated with more prestigious universities. Most of the information on the educational backgrounds is in one way or the other self-reported by the respective founders and investors, which makes it more likely that graduates from less prestigious institutions do not report their university track record. However, if this is the case top-university ties could be overrepresented in the sample which would most likely lead to an underestimation of the effect of educational ties. While it cannot be ruled out totally that this is the case, I mitigate the issue in three ways. First, as described in section 4.3 my primary data source Crunchbase does among other channels rely on a dedicated in-house team to collect and curate its data making it less likely that self-reporting issues bias their data. Second, with the addition of LinkedIn data, I substantially increase the variety of university affiliations in the data increasing the representativity of the sample. And third, I empirically account for this potential bias by separately looking at the effect of top and non-top university ties as well as by including scaled versions of the educational tie dummies that consider the level of exclusivity of a tie.

The second limitation only concerns the matching analysis. Due to the counterfactual methodology, the narrow definition of educational ties is not applicable when analyzing the likelihood of investment. I construct the counterfactuals on the startup-VC-firm level. As I do not take any presumption on which of the partners at the VC firm acts as the investment partner for the counterfactual observations the narrowly-defined educational tie variables are not available for the analysis. Thus, it is probable that the broad definition involving all VC partners identifies too many educational ties for the actual investments. This makes it likely that the overall effect of an educational tie on the likelihood of investing is underestimated in the regressions.

Third, the results of the investment success analysis in section 4.4.4 have to be interpreted with caution. While I control for several determinants influencing the IPO probability (e.g. startup and investor characteristics via fixed effects), likely, not all determinants of exit success are perfectly controlled for. There is no viable way to control for e.g. the quality of the founder's original idea. This limitation prevents me from fully differentiating between selection and treatment effects as the explanation of the positive relationship between educational ties and the likelihood of an IPO.

4.5 Conclusion

Famously, the venture capital industry is a tight knight community. Due to the high level of information asymmetry potential investors are faced with, venture capital investments are much more dependent on trust and confidence among a small group of individuals on both sides of a deal than other investments. Consequently, information asymmetry between founders seeking an investor and venture capital partners looking for promising investments is a big obstacle in the formation of funding relationships that needs to be overcome. This paper explores the role and value of university affiliations of both investors and founders in mitigating information asymmetry in venture capital funding relationships.

University affiliations might affect the initial matching process and the subsequent funding relationship between founders and venture capitalists via two mechanisms. First, attending top universities might build and signal founders‘ human capital to investors allowing them to identify better investment targets with more confidence. Second, belonging to the same alumni network might decrease information asymmetry via improved information flow and a higher level of generalized trust between founders and investors. This paper's main focus lies in exploring the second mechanism. I exploit a novel and unique sample of 42,101 venture capital investments based on data from Crunchbase and LinkedIn that comprises 38,452 individuals with 58,508 university affiliations. The sample allows controlling for various alternative explanations, especially via startup and investor fixed effects. While results confirm that founders affiliated with top universities are about 5% more likely to receive funding, the relative increase of the likelihood of investing attributable to educational ties of more than 25% is over 5 times higher. The first key contribution of the paper is the analysis of educational ties at different granularity levels. The results show that educational ties positively affect the matching process irrespective of the university's quality and can be confirmed for U.S. and European universities alike. Further, educational ties are more valuable the more exclusive they are and redundant ties have a diminishing value for the investment decision. The second key contribution of the paper is the analysis of the effect of educational ties on the full startup lifecycle. Investors are more likely to lead an investment syndicate, take a board seat, and invest in a startup's first funding round in the presence of educational ties. Furthermore, given an educational tie, they stay invested for more funding rounds and invest in younger companies. Finally, results indicate that when investors and founders are part of the same alumni network startups are more likely to eventually go public. These findings are all consistent with the notion that alumni networks as a special form of social networks do improve collaboration and information flow between individuals leading to more informed investment and business decisions and ultimately better investment outcomes. At the same time, the results clearly repudiate pure favoritism as an alternative explanation of the positive effect of educational ties on the matching process.

While this paper provides ample evidence for the role of educational ties in venture capital, some interesting research questions remain unanswered. It would be worthwhile to find out whether some venture capital firms are more likely to tilt their portfolio towards founders from their alumni network than others. To answer that question a VC-firm-level analysis is necessary. Do venture capital funds with a higher share of deals involving educational ties outperform or underperform their peers? Further, some universities offer dedicated accelerator programs or similar initiatives to actively foster the entrepreneurial community at the university. It would be interesting to find out, how effective these programs are. Are these programs increasing the frequency of educational ties stemming from the respective universities? Finally, this paper focuses on the U.S. and European venture capital firms. However, it would also be relevant if the findings can be confirmed for the rising Chinese venture capital market. Answers to these questions would further advance the literature on the role of educational ties in venture capital. I will leave these questions open for further research.

5 Conclusion

As highlighted in chapter 1 the amount of venture capital spending has increased drastically over the last decades. While the importance of the sector has grown, it is nowhere near as regulated as public markets. Further, the number of people working as venture capital investors has remained quite small, which is one reason for the notoriously tight-knit entrepreneurial finance community of investors and entrepreneurs. Consequently, the venture capital environment is full of interesting agency problems worthwhile to study. This thesis advances the knowledge about select agency problems in venture capital in each included essay.

In chapter 2 we introduce the potential agency conflict between limited partners and general partners caused by investment style drifts. The article scrutinizes the question of why limited partners are concerned about style drifts but do not contractually rule them out. Investment style drifts are defined as deviations from a venture capital fund's expected investment style, which is used by limited partners as the basis for their capital allocation. The article contributes in three main ways to the understanding of style drifts in venture capital, which is a relatively understudied topic in the literature.

First, it extends prior literature on investment stage drifts by examining style drifts in all three core investment style dimensions (portfolio company development stage, location, and industry). Second, it distinguishes between style drifts out of necessity and those that are deliberate risk-taking decisions and connects all three style drifting dimensions to the underlying risk-taking attitude of venture capitalists. In the article, we hypothesize that when general partners deviate from the expected investment style, they may not act in the best interest of limited partners because style drifts represent shifts in the risk-return profile of a fund. The findings suggest that style drifts are likely to represent an agency conflict because results support the hypothesis that compensation incentives outweigh employment incentives for well-performing venture capitalists. Well-performing venture capitalists increase investment risk to benefit from higher compensation potential via carried interest when they feel confident they will be able to raise a follow-on fund securing their base income via management fees. Third, the article analyzes the impact of style drifts on individual investment and fund performance. The results show that aggregate style drifts negatively impact a fund's exit rate, confirming the risk implications of style drifts.

In the second essay presented in chapter 3 we focus on the role of information asymmetry in funding relationships between entrepreneurs and venture capitalists. We discuss the various mechanisms (screening, due diligence, and monitoring) that venture capitalists use to mitigate the risk of adverse selection. The staging of investments can be an effective strategy for venture capitalists to reduce information asymmetry and improve the chances of successful investments. Staged investments make it necessary for entrepreneurs to periodically provide updates in each funding round to investors on the company's progress. In the article, we empirically scrutinize how the content and specificity of the provided informational updates under different levels of information asymmetry are incorporated into the venture capitalists' valuation processes. So far, work in this area has been purely theoretical without empirical confirmation.

The article has two main contributions with relevance for entrepreneurs in practice. First, we find empirical evidence that the valuation impact of negative information signals can be offset by the entrepreneur through the provision of highly specific information. Second, the value of an informational update is influenced by the prevailing level of information asymmetry between the investor syndicate and the entrepreneur. When there is a higher level of information asymmetry, i.e. when there is no incumbent investor in the syndicate, both positive and negative information signals have a greater impact on valuations.

The third and final essay included in chapter 4 puts the focus on the educational background and the educational ties of founders and venture capitalists as one factor that might reduce information asymmetry. University affiliations offer two channels that might influence the funding relationship between founders and venture capitalists. First, graduating from a top university might act as a founder-quality signal helping venture capitalists in the selection process. Second, belonging to the same alumni network might cultivate generalized trust, establish effective incentives through punishment and rewards, and facilitate the exchange of information among alumni. I examine the value of educational ties between founders and investors over the entire venture capital funding process, from the initial matching between startup and venture capital firm to the depth of the ongoing relationship to the eventual startup performance and investment exit success of the investor.

The main contributions and results are as follows: Results show that educational ties have a positive effect on the venture capital funding process, including the initial matching, the involvement of the investor during the funding relationship, and the eventual startup performance and investment exit success. Educational ties are more valuable the more exclusive they are and redundant ties have a diminishing value for the investment decision. The empirical evidence indicates that educational ties are related to ultimately better investment outcomes. Thus, the results clearly repudiate pure favoritism as an alternative explanation of the positive effect of educational ties on the matching process. Educational ties improve collaboration and information flow between individuals, leading to fewer agency issues and thus to more informed portfolio selection and better business decisions.

As this thesis has demonstrated, agency problems in venture capital are an important and complex issue that can have significant consequences for both venture capitalists and the firms they fund. While this thesis provides answers to the specific questions in each essay, further research could shed more light on additional issues to better understand the factors that contribute to agency problems in venture capital, as well as the most effective strategies for mitigating these problems. Further research could elaborate and answer some of the following interesting questions: How do different governance structures affect the alignment of interests between venture capitalists and the firms they fund? Is performance-based compensation effective at aligning the interests of venture capitalists with those of the firms they fund? How does the reputation of venture capital firms and individual venture capitalists influence the occurrence and impact of agency problems? How do social networks other than alumni networks within the venture capital industry impact agency problems? And, which regulatory interventions are effective at reducing agency problems in the venture capital industry? I will leave these questions open for further research.

Bibliography

Admati, Anat R. and Paul Pfleiderer (1994). "Robust Financial Contracting and the Role of Venture Capitalists". In: *The Journal of Finance* 49.2, pp. 371–402. DOI: 10.1111/j.1540-6261.1994.tb05146.x (cited on pages 58, 68, 84).

Aizawa, Akiko (2003). "An information-theoretic perspective of tf–idf measures". In: *Information Processing & Management* 39.1, pp. 45–65. DOI: 10.1016/S0306-4573(02)00021-3 (cited on page 67).

Akerlof, George A. (1970). "The Market for "Lemons": Quality Uncertainty and the Market Mechanism". In: *The Quarterly Journal of Economics* 84.3, pp. 488–500. DOI: 10.2307/1879431 (cited on pages 12, 59, 84).

Alessia, D, Fernando Ferri, Patrizia Grifoni, and Tiziana Guzzo (2015). "Approaches, tools and applications for sentiment analysis implementation". In: *International Journal of Computer Applications* 125.3. DOI: 10.5120/ijca2015905866 (cited on page 64).

Alexy, Oliver, Joern Block, Philipp Sandner, and Anne L.J. Wal (2012). "Social capital of venture capitalists and start-up funding". In: *Small Business Economics* 39.4, pp. 835–851. DOI: 10.1007/s11187-011-9337-4 (cited on page 90).

Ali, Ashiq, Sandy Klasa, and Eric Yeung (2014). "Industry concentration and corporate disclosure policy". In: *Journal of Accounting and Economics* 58.2, pp. 240–264. DOI: 10.1016/j.jacceco.2014.08.004 (cited on page 61).

Amit, Raphael, James Brander, and Christoph Zott (1998). "Why do venture capital firms exist? theory and canadian evidence". In: *Journal of Business Venturing* 13.6, pp. 441–466. DOI: 10.1016/S0883-9026(97)00061-X (cited on page 60).

Arcidiacono, Peter, Patrick Bayer, and Aurel Hizmo (2010). "Beyond Signaling and Human Capital: Education and the Revelation of Ability". In: *American Economic Journal: Applied Economics* 2.4, pp. 76–104. DOI: 10.1257/app.2.4.76 (cited on page 86).

Arcot, Sridhar (2014). "Participating convertible preferred stock in venture capital exits". In: *Journal of Business Venturing* 29.1, pp. 72–87. DOI: 10.1016/j.jbusvent.2013.06.001 (cited on page 59).

Baker, Malcolm and Jeffrey Wurgler (2007). "Investor Sentiment in the Stock Market". In: *Journal of Economic Perspectives* 21.2, pp. 129–152. DOI: 10.1257/jep.21.2.129 (cited on page 64).

Banerji, Devika and Torsten Reimer (2019). “Startup founders and their LinkedIn connections: Are well-connected entrepreneurs more successful?” In: *Computers in Human Behavior* 90, pp. 46–52. DOI: 10.1016/j.chb.2018.08.033 (cited on page 93).

Barberis, Nicholas and Andrei Shleifer (2003). “Style investing”. In: *Journal of Financial Economics* 68.2, pp. 161–199. DOI: 10.1016/s0304-405x(03)00064-3 (cited on page 8).

Barry, Christopher B., Chris J. Muscarella, John W. Peavy, and Michael R. Vetsuypens (1990). “The role of venture capital in the creation of public companies: Evidence from the going-public process”. In: *Journal of Financial Economics* 27.2, pp. 447–471. DOI: 10.1016/0304-405X(90)90064-7 (cited on page 89).

Bengtsson, Ola and David H Hsu (2010). “How do venture capital partners match with startup founders?” Working Paper available at SSRN. DOI: 10.2139/ssrn.1568131 (cited on pages 85, 91).

Bengtsson, Ola and David H. Hsu (2015). “Ethnic matching in the U.S. venture capital market”. In: *Journal of Business Venturing* 30.2, pp. 338–354. DOI: 10.1016/j.jbusvent.2014.09.001 (cited on pages 22, 85, 89, 90, 93, 98, 121).

Bengtsson, Ola, Steven N. Kaplan, Frederic Martel, and Per Strömberg (2005). “Investment screening and market conditions: Evidence from venture capital”. Working Paper available at SSRN. DOI: 10.2139/ssrn.890175 (cited on page 16).

Bergemann, Dirk and Ulrich Hege (1998). “Venture capital financing, moral hazard, and learning”. In: *Journal of Banking & Finance* 22.6, pp. 703–735. DOI: 10.1016/S0378-4266(98)00017-X (cited on pages 58, 59, 62).

Bergemann, Dirk, Ulrich Hege, and Liang Peng (2010). “Venture capital and sequential investments”. In: *Available at SSRN 1572103*. DOI: 10.2139/ssrn.1295339 (cited on pages 59, 60).

Berkowitz, Daniel, Katharina Pistor, and Jean-Francois Richard (2003). “Economic development, legality, and the transplant effect”. In: *European Economic Review* 47.1, pp. 165–195. DOI: 10.1016/s0014-2921(01)00196-9 (cited on pages 19, 23, 46).

Bernstein, Shai, Xavier Giroud, and Richard R. Townsend (2016). “The Impact of Venture Capital Monitoring”. In: *The Journal of Finance* 71.4, pp. 1591–1622. DOI: 10.1111/jofi.12370 (cited on pages 11, 60, 61).

Bhave, Mahesh P. (1994). “A process model of entrepreneurial venture creation”. In: *Journal of Business Venturing* 9.3, pp. 223–242. DOI: 10.1016/0883-9026(94)90031-0 (cited on pages 58, 64).

Bird, Steven, Ewan Klein, and Edward Loper (2009). *Natural language processing with Python: analyzing text with the natural language toolkit*. O’Reilly Media, Inc. (cited on page 67).

Bollazzi, Francesco, Giuseppe Risalvato, and Claudio Venezia (2019). "Asymmetric information and deal selection: evidence from the Italian venture capital market". In: *International Entrepreneurship and Management Journal* 15.3, pp. 721–732. DOI: 10.1007/s11365-018-0539-y (cited on page 60).

Bottazzi, Laura, Marco Da Rin, and Thomas Hellmann (2016). "The Importance of Trust for Investment: Evidence from Venture Capital". In: *The Review of Financial Studies* 29.9, pp. 2283–2318. DOI: 10.1093/rfs/hhw023 (cited on pages 63, 88, 117).

Bottazzi, Laura, Marco Da Rin, and Thomas Hellmann (2008). "Who are the active investors?: Evidence from venture capital". In: *Journal of Financial Economics* 89.3, pp. 488–512. DOI: 10.1016/j.jfineco.2007.09.003 (cited on pages 21, 121).

Brown, Gregory W., Oleg R. Gredil, and Steven N. Kaplan (2019). "Do private equity funds manipulate reported returns?" In: *Journal of Financial Economics* 132.2, pp. 267–297. DOI: 10.1016/j.jfineco.2018.10.011 (cited on page 9).

Brown, Keith C., W. Van Harlow W., and Laura T. Starks (1996). "Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry". In: *The Journal of Finance* 51.1, pp. 85–110. DOI: 10.1111/j.1540-6261.1996.tb05203.x (cited on pages 9, 14).

Brown, Keith C., W. Van Harlow, and Hanjiang Zhang (2009). "Staying the course: mutual fund investment style consistency and performance persistence". Working Paper available at SSRN. DOI: 10.2139/ssrn.1364737 (cited on page 8).

Bubna, Amit, Sanjiv R. Das, and Paul Hanouna (2020). "The Fast and the Curious: VC Drift". In: *Journal of Financial Services Research* 57.1, pp. 69–113. DOI: 10.1007/s10693-018-0302-0 (cited on pages 8, 13, 14, 18, 44, 54).

Buzzacchi, Luigi, Giuseppe Scellato, and Elisa Ughetto (2015). "Investment stage drifts and venture capital managerial incentives". In: *Journal of Corporate Finance* 33, pp. 118–128. DOI: 10.1016/j.jcorpfin.2015.05.006 (cited on pages 8, 11, 13, 16, 20, 44).

Bygrave, William D. (1987). "Syndicated investments by venture capital firms: A networking perspective". In: *Journal of Business Venturing* 2.2, pp. 139–154. DOI: 10.1016/0883-9026(87)90004-8 (cited on page 70).

Chahine, Salim, Samer Saade, and Marc Goergen (2019). "Foreign Business Activities, Foreignness of the VC Syndicate, and IPO Value". In: *Entrepreneurship Theory and Practice* 43.5, pp. 947–973. DOI: 10.1177/1042258718757503 (cited on page 93).

Chakraborty, Indraneel and Michael Ewens (2018). "Managing Performance Signals Through Delay: Evidence from Venture Capital". In: *Management Science* 64.6, pp. 2875–2900. DOI: 10.1287/mnsc.2016.2662 (cited on page 9).

Chan, Louis K. C., Hsiu-Lang Chen, and Josef Lakonishok (2002). "On Mutual Fund Investment Styles". In: *The Review of Financial Studies* 15.5, pp. 1407–1437. DOI: 10.1093/rfs/15.5.1407 (cited on page 8).

Chemmanur, Thomas J., Karthik Krishnan, and Debarshi K. Nandy (2011). “How Does Venture Capital Financing Improve Efficiency in Private Firms? A Look Beneath the Surface”. In: *The Review of Financial Studies* 24.12, pp. 4037–4090. DOI: 10.1093/rfs/hhr096 (cited on page 12).

Chen, Jing and Peter Thompson (2015). “New Firm Performance and the Replacement of Founder-CEOs”. In: *Strategic Entrepreneurship Journal* 9.3, pp. 243–262. DOI: 10.1002/sej.1203 (cited on page 84).

Chenlo, Jose M. and David E. Losada (2014). “An empirical study of sentence features for subjectivity and polarity classification”. In: *Information Sciences* 280, pp. 275–288. DOI: 10.1016/j.ins.2014.05.009 (cited on page 64).

Chevalier, Judith and Glenn Ellison (1997). “Risk Taking by Mutual Funds as a Response to Incentives”. In: *Journal of Political Economy* 105.6, pp. 1167–1200. DOI: 10.1086/516389 (cited on page 14).

Chevalier, Judith and Glenn Ellison (1999a). “Are Some Mutual Fund Managers Better Than Others? Cross-Sectional Patterns in Behavior and Performance”. In: *The Journal of Finance* 54.3, pp. 875–899. DOI: 10.1111/0022-1082.00130 (cited on pages 84, 87).

Chevalier, Judith and Glenn Ellison (1999b). “Career Concerns of Mutual Fund Managers”. In: *The Quarterly Journal of Economics* 114.2, pp. 389–432. DOI: 10.1162/003355399556034 (cited on page 15).

Chircop, Justin, Sofia Johan, and Monika Tarsalewska (2020). “Does religiosity influence venture capital investment decisions?” In: *Journal of Corporate Finance* 62, p. 101589. DOI: 10.1016/j.jcorpfin.2020.101589 (cited on page 11).

Chung, Ji-Woong, Berk A. Sensoy, Léa Stern, and Michael S. Weisbach (2012). “Pay for Performance from Future Fund Flows: The Case of Private Equity”. In: *The Review of Financial Studies* 25.11, pp. 3259–3304. DOI: 10.1093/rfs/hhr141 (cited on page 15).

Cochrane, John H. (2005). “The risk and return of venture capital”. In: *Journal of Financial Economics* 75.1, pp. 3–52. DOI: 10.1016/j.jfineco.2004.03.006 (cited on pages 10, 11, 17, 63, 89, 101, 117).

Cohen, Lauren, Andrea Frazzini, and Christopher Malloy (2010). “Sell-Side School Ties”. In: *The Journal of Finance* 65.4, pp. 1409–1437. DOI: 10.1111/j.1540-6261.2010.01574.x (cited on pages 85, 88).

Coleman, James S (1994). *Foundations of social theory*. Harvard university press (cited on page 88).

Coleman, James S. (1988). “Social Capital in the Creation of Human Capital”. In: *American Journal of Sociology* 94, S95–s120. DOI: 10.1086/228943 (cited on page 86).

Colombo, Massimo G., Massimiliano Guerini, Cristina Rossi-Lamastra, and Andrea Bonaccorsi (2022). "The "first match"between high-tech entrepreneurial ventures and universities: the role of founders'social ties". In: *The Journal of Technology Transfer* 47.1, pp. 270–306. DOI: 10.1007/s10961-021-09848-3 (cited on page 110).

Cooney, John W., Leonardo Madureira, Ajai K. Singh, and Ke Yang (2015). "Social ties and IPO outcomes". In: *Journal of Corporate Finance* 33, pp. 129–146. DOI: 10.1016/j.jcorpfin.2015.05.003 (cited on pages 85, 88).

Cornelli, Francesca and Oved Yosha (2003). "Stage Financing and the Role of Convertible Securities". In: *The Review of Economic Studies* 70.1, pp. 1–32. DOI: 10.1111/1467-937X.00235 (cited on pages 58, 84).

Corwin, Shane A. and Paul Schultz (2005). "The Role of IPO Underwriting Syndicates: Pricing, Information Production, and Underwriter Competition". In: *The Journal of Finance* 60.1, pp. 443–486. DOI: 10.1111/j.1540-6261.2005.00735.x (cited on pages 98, 110).

Cox Pahnke, Emily, Rory McDonald, Dan Wang, and Benjamin Hallen (2014). "Exposed: Venture Capital, Competitor Ties, and Entrepreneurial Innovation". In: *Academy of Management Journal* 58.5, pp. 1334–1360. DOI: 10.5465/amj.2012.0777 (cited on page 61).

Crain, Nicholas G. (2018). "Venture capital and career concerns". In: *Journal of Corporate Finance* 49, pp. 168–185. DOI: 10.1016/j.jcorpfin.2017.12.004 (cited on page 15).

Cumming, Douglas (2006). "Adverse Selection and Capital Structure: Evidence from Venture Capital". In: *Entrepreneurship Theory and Practice* 30.2, pp. 155–183. DOI: 10.1111/j.1540-6520.2006.00116.x (cited on pages 18, 60).

Cumming, Douglas and Na Dai (2010). "Local bias in venture capital investments". In: *Journal of Empirical Finance* 17.3, pp. 362–380. DOI: 10.1016/j.jempfin.2009.11.001 (cited on pages 12, 103).

Cumming, Douglas and Na Dai (2013). "Why Do Entrepreneurs Switch Lead Venture Capitalists?" In: *Entrepreneurship Theory and Practice* 37.5, pp. 999–1017. DOI: 10.1111/j.1540-6520.2012.00525.x (cited on page 72).

Cumming, Douglas, Grant Fleming, and Armin Schwienbacher (2005). "Liquidity Risk and Venture Capital Finance". In: *Financial Management* 34.4, pp. 77–105. DOI: 10.1111/j.1755-053X.2005.tb00119.x (cited on page 10).

Cumming, Douglas, Grant Fleming, and Armin Schwienbacher (2006). "Legality and venture capital exits". In: *Journal of Corporate Finance* 12.2, pp. 214–245. DOI: 10.1016/j.jcorpfin.2004.12.004 (cited on page 46).

Cumming, Douglas, Grant Fleming, and Armin Schwienbacher (2009). "Style Drift in Private Equity". In: *Journal of Business Finance & Accounting* 36.5-6, pp. 645–678. DOI: 10.1111/j.1468-5957.2009.02137.x (cited on pages 8, 13, 17–20, 101).

Cumming, Douglas, Irene Henriques, and Perry Sadorsky (2016a). "'Cleantech' venture capital around the world". In: *International Review of Financial Analysis* 44, pp. 86–97. DOI: 10.1016/j.irfa.2016.01.015 (cited on page 43).

Cumming, Douglas and Sofia A. Johan (2013). *Venture Capital and Private Equity Contracting - An International Perspective*. Amsterdam, Boston: Academic Press (cited on page 16).

Cumming, Douglas, April Knill, and Kelsey Syvrud (2016b). "Do international investors enhance private firm value? Evidence from venture capital". In: *Journal of International Business Studies* 47.3, pp. 347–373. DOI: 10.1057/jibs.2015.46 (cited on page 21).

Cumming, Douglas and Silvio Vismara (2017). "De-segmenting research in entrepreneurial finance". In: *Venture Capital* 19.1-2, pp. 17–27. DOI: 10.1080/13691066.2016.1225910 (cited on page 2).

Cumming, Douglas, Uwe Walz, and Jochen Christian Werth (2014). "Entrepreneurial Spawning: Experience, Education, and the Role of Venture Capital". Working Paper available at SSRN. DOI: http://dx.doi.org/10.2139/ssrn.2503532 (cited on page 90).

Das, Sanjiv R., Hoje Jo, and Yongtae Kim (2011). "Polishing diamonds in the rough: The sources of syndicated venture performance". In: *Journal of Financial Intermediation* 20.2, pp. 199–230. DOI: 10.1016/j.jfi.2010.08.001 (cited on page 121).

Dedman, Elisabeth and Clive Lennox (2009). "Perceived competition, profitability and the withholding of information about sales and the cost of sales". In: *Journal of Accounting and Economics* 48.2, pp. 210–230. DOI: 10.1016/j.jacceco.2009.07.003 (cited on page 61).

Dierkens, Nathalie (1991). "Information Asymmetry and Equity Issues". In: *Journal of Financial and Quantitative Analysis* 26.2, pp. 181–199. DOI: 10.2307/2331264 (cited on page 62).

Diller, Christian and Christoph Kaserer (2009). "What Drives Private Equity Returns? – Fund Inflows, Skilled GPs, and/or Risk?" In: *European Financial Management* 15.3, pp. 643–675. DOI: 10.1111/j.1468-036X.2007.00438.x (cited on pages 11, 16).

Dittmann, Ingolf, Ernst Maug, and Johannes Kemper (2004). "How Fundamental are Fundamental Values? Valuation Methods and their Impact on the Performance of German Venture Capitalists". In: *European Financial Management* 10.4, pp. 609–638. DOI: 10.1111/j.1354-7798.2004.00268.x (cited on page 65).

Dixit, Avinash K. and Robert S. Pindyck (1994). *Investment under Uncertainty*. Princeton University Press. DOI: 10.2307/j.ctt7sncv (cited on page 61).

Dubocage, Emmanuelle and Géraldine Galindo (2014). "Understanding founder–CEO's replacement in venture-backed companies: A theoretical and empirical analysis". In: *European Management Journal* 32.3, pp. 461–474. DOI: 10.1016/j.emj.2013.11.003 (cited on page 84).

Ellis, Jesse A, C Edward Fee, and Shawn E Thomas (2012). "Proprietary costs and the disclosure of information about customers". In: *Journal of Accounting Research* 50.3, pp. 685–727. DOI: 10.1111/j.1475-679X.2012.00441.x (cited on page 61).

Emery, Kenneth M (2003). "Private Equity Risk and Reward". In: *The Journal of Private Equity* 6.2, pp. 43–50. DOI: 10.3905/jpe.2003.320038 (cited on page 11).

Engelberg, Joseph, Pengjie Gao, and Christopher A. Parsons (2012). "Friends with money". In: *Journal of Financial Economics* 103.1, pp. 169–188. DOI: 10.1016/j.jfineco.2011.08.003 (cited on pages 85, 88).

Ewens, Michael and Matthew Rhodes-Kropf (2015). "Is a VC Partnership Greater Than the Sum of Its Partners?" In: *The Journal of Finance* 70.3, pp. 1081–1113. DOI: 10.1111/jofi.12249 (cited on page 63).

Fracassi, Cesare (2017). "Corporate Finance Policies and Social Networks". In: *Management Science* 63.8, pp. 2420–2438. DOI: 10.1287/mnsc.2016.2433 (cited on page 90).

Fried, Vance H. and Robert D. Hisrich (1994). "Toward a Model of Venture Capital Investment Decision Making". In: *Financial Management* 23.3, pp. 28–37. DOI: 10.2307/3665619 (cited on pages 18, 60).

Fuchs, Florian, Roland Füss, Tim Jenkinson, and Stefan Morkoetter (2021). "Winning a deal in private equity: Do educational ties matter?" In: *Journal of Corporate Finance* 66, p. 101740. DOI: 10.1016/j.jcorpfin.2020.101740 (cited on pages 85, 88, 96, 98, 110).

Fuchs, Florian, Roland Füss, Tim Jenkinson, and Stefan Morkoetter (2022). "Should Investors Care Where Private Equity Managers Went to School?" In: *Review of Corporate Finance* 2.3, pp. 451–492. DOI: 10.1561/114.00000021 (cited on pages 84, 87).

Gaddy, Benjamin E., Varun Sivaram, Timothy B. Jones, and Libby Wayman (2017). "Venture Capital and Cleantech: The wrong model for energy innovation". In: *Energy Policy* 102, pp. 385–395. DOI: 10.1016/j.enpol.2016.12.035 (cited on page 90).

Garg, Sam and Nathan Furr (2017). "Venture Boards: Past Insights, Future Directions, and Transition to Public Firm Boards". In: *Strategic Entrepreneurship Journal* 11.3, pp. 326–343. DOI: 10.1002/sej.1258 (cited on page 89).

Gartner, William B. (1985). "A Conceptual Framework for Describing the Phenomenon of New Venture Creation". In: *The Academy of Management Review* 10.4, pp. 696–706. DOI: 10.2307/258039 (cited on pages 58, 64).

Gladstone, David and Laura Gladstone (2002). *Venture capital handbook: an entrepreneur's guide to raising venture capital.* FT Press (cited on page 87).

Gompers, Paul A. (1994). "The Rise and Fall of Venture Capital". In: *Business and Economic History* 23.2, pp. 1–26. DOI: 10.2307/23702914 (cited on page 19).

Gompers, Paul A. (1995). "Optimal Investment, Monitoring, and the Staging of Venture Capital". In: *The Journal of Finance* 50.5, pp. 1461–1489. DOI: 10.1111/j.1540-6261.1995.tb05185.x (cited on pages 60, 61).

Gompers, Paul A. (1996). "Grandstanding in the venture capital industry". In: *Journal of Financial Economics* 42.1, pp. 133–156. DOI: 10.1016/0304-405x(96)00874-4 (cited on pages 17, 101).

Gompers, Paul A., Will Gornall, Steven N. Kaplan, and Ilya A. Strebulaev (2020). "How do venture capitalists make decisions?" In: *Journal of Financial Economics* 135.1, pp. 169–190. DOI: 10.1016/j.jfineco.2019.06.011 (cited on pages 18, 84, 93, 97).

Gompers, Paul A., Anna Kovner, and Josh Lerner (2009). "Specialization and Success: Evidence from Venture Capital". In: *Journal of Economics & Management Strategy* 18.3, pp. 817–844. DOI: 10.1111/j.1530-9134.2009.00230.x (cited on pages 12, 63).

Gompers, Paul A., Anna Kovner, Josh Lerner, and David Scharfstein (2006). "Skill vs. Luck in Entrepreneurship and Venture Capital: Evidence from Serial Entrepreneurs". In: *National Bureau of Economic Research*. Working Paper Series 12592. DOI: 10.3386/w12592 (cited on page 72).

Gompers, Paul A., Anna Kovner, Josh Lerner, and David Scharfstein (2010). "Performance persistence in entrepreneurship". In: *Journal of Financial Economics* 96.1, pp. 18–32. DOI: 10.1016/j.jfineco.2009.11.001 (cited on pages 103, 124).

Gompers, Paul A. and Josh Lerner (1997). "Risk and Reward in Private Equity Investments: The Challenge of Performance Assessment". In: *The Journal of Private Equity* 1.2, pp. 5–12. DOI: 10.3905/jpe.1997.409670 (cited on page 11).

Gompers, Paul A. and Josh Lerner (2000a). "Money chasing deals? The impact of fund inflows on private equity valuations". In: *Journal of Financial Economics* 55.2, pp. 281–325. DOI: 10.1016/s0304-405x(99)00052-5 (cited on pages 16, 17, 25, 73).

Gompers, Paul A. and Josh Lerner (2000b). "The Determinants of Corporate Venture Capital Success: Organizational Structure, Incentives, and Complementarities". In: *Concentrated Corporate Ownership*. University of Chicago Press, pp. 17–54 (cited on pages 22, 121).

Gompers, Paul A. and Josh Lerner (2001). *The money of invention: How venture capital creates new wealth*. Harvard Business School Press (cited on page 87).

Gompers, Paul A., Vladimir Mukharlyamov, and Yuhai Xuan (2016). "The cost of friendship". In: *Journal of Financial Economics* 119.3, pp. 626–644. DOI: 10.1016/j.jfineco.2016.01.013 (cited on pages 19, 85, 88, 90, 93, 96, 98).

Gorman, Michael and William A. Sahlman (1989). "What do venture capitalists do?" In: *Journal of Business Venturing* 4.4, pp. 231–248. DOI: 10.1016/0883-9026(89)90014-1 (cited on page 89).

Gottesman, Aron A. and Matthew R. Morey (2006). "Manager education and mutual fund performance". In: *Journal of Empirical Finance* 13.2, pp. 145–182. DOI: 10.1016/j.jempfin.2005.10.001 (cited on pages 84, 87).

Granovetter, Mark (2005). “The Impact of Social Structure on Economic Outcomes”. In: *The Journal of Economic Perspectives* 19.1, pp. 33–50. DOI: 10.1257/0895330053147958 (cited on page 87).

Greene, William H. (2018). *Econometric Analysis*. 8th. Amsterdam: Pearson Education (cited on page 50).

Grossman, Sanford J. (1981). “The Informational Role of Warranties and Private Disclosure about Product Quality”. In: *The Journal of Law & Economics* 24.3, pp. 461–483. DOI: 10.1086/466995 (cited on pages 60–62).

Gulen, Huseyin and Mihai Ion (2016). “Policy Uncertainty and Corporate Investment”. In: *The Review of Financial Studies* 29.3, pp. 523–564. DOI: 10.1093/rfs/hhv050 (cited on page 64).

Hansen, Stephen and Michael McMahon (2016). “Shocking language: Understanding the macroeconomic effects of central bank communication”. In: *Journal of International Economics* 99, S114–s133. DOI: 10.1016/j.jinteco.2015.12.008 (cited on page 64).

Hart, Oliver (1995). *Firms, contracts, and financial structure*. Clarendon press (cited on page 2).

Heckman, James J. (1976). “The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models”. In: *Annals of economic and social measurement, volume 5, number 4*. Nber, pp. 475–492 (cited on page 73).

Heckman, James J. (1978). “Dummy Endogenous Variables in a Simultaneous Equation System”. In: *Econometrica* 46.4, pp. 931–959. DOI: 10.2307/1909757 (cited on page 50).

Heckman, James J. (1979). “Sample Selection Bias as a Specification Error”. In: *Econometrica* 47.1, pp. 153–161. DOI: 10.2307/1912352 (cited on pages 64, 73).

Hegde, Deepak and Justin Tumlinson (2014). “Does Social Proximity Enhance Business Partnerships? Theory and Evidence from Ethnicity’s Role in U.S. Venture Capital”. In: *Management Science* 60.9, pp. 2355–2380. DOI: 10.1287/mnsc.2013.1878 (cited on page 88).

Hellmann, Thomas (2006). “IPOs, acquisitions, and the use of convertible securities in venture capital”. In: *Journal of Financial Economics* 81.3, pp. 649–679. DOI: 10.1016/j.jfineco.2005.06.007 (cited on page 59).

Hochberg, Yael, Alexander Ljungqvist, and Yang Lu (2007). “Whom You Know Matters: Venture Capital Networks and Investment Performance”. In: *The Journal of Finance* 62.1, pp. 251–301. DOI: 10.1111/j.1540-6261.2007.01207.x (cited on pages 22, 25, 50, 51, 101).

Hofstede, Geert H. (2001). *Culture’s consequences: Comparing values, behaviors, institutions, and organizations across nations*. 2nd and enlarged. Thousand Oaks, CA: Sage (cited on pages 19, 23, 43).

Holmström, Bengt (1979). "Moral Hazard and Observability". In: *The Bell Journal of Economics* 10.1, pp. 74–91. DOI: 10.2307/3003320 (cited on page 62).

Hsu, Yao-Wen (2010). "Staging of venture capital investment: a real options analysis". In: *Small Business Economics* 35.3, pp. 265–281. DOI: 10.1007/s11187-008-9158-2 (cited on pages 58, 59).

Hull, Tyler (2018). "Why Venture Capitalists Stray From Their Industry Comfort Zones". Working Paper. DOI: 10.2139/ssrn.3303466 (cited on page 17).

Inderst, Roman and Holger M. Müller (2004). "The effect of capital market characteristics on the value of start-up firms". In: *Journal of Financial Economics* 72.2, pp. 319–356. DOI: 10.1016/j.jfineco.2003.06.001 (cited on pages 16, 36).

Ishii, Joy and Yuhai Xuan (2014). "Acquirer-target social ties and merger outcomes". In: *Journal of Financial Economics* 112.3, pp. 344–363. DOI: 10.1016/j.jfineco.2014.02.007 (cited on page 90).

Jenkinson, Tim, Miguel Sousa, and Rüdiger Stucke (2013). "How fair are the valuations of private equity funds?" Working Paper. DOI: 10.2139/ssrn.2229547 (cited on page 9).

Jensen, Michael C. and William H. Meckling (1976). "Theory of the firm: Managerial behavior, agency costs and ownership structure". In: *Journal of Financial Economics* 3.4, pp. 305–360. DOI: 10.1016/0304-405x(76)90026-x (cited on pages 60, 84, 121).

Kaplan, Steven N. and Josh Lerner (2016). *Venture capital data: Opportunities and challenges*. Working Paper 22500. National Bureau of Economic Research. DOI: 10.3386/w22500 (cited on page 19).

Kaplan, Steven N. and Antoinette Schoar (2005). "Private Equity Performance: Returns, Persistence, and Capital Flows". In: *The Journal of Finance* 60.4, pp. 1791–1823. DOI: 10.1111/j.1540-6261.2005.00780.x (cited on pages 22, 54).

Kaplan, Steven N., Berk A. Sensoy, and Per Strömberg (2009). "Should Investors Bet on the Jockey or the Horse? Evidence from the Evolution of Firms from Early Business Plans to Public Companies". In: *The Journal of Finance* 64.1, pp. 75–115. DOI: 10.1111/j.1540-6261.2008.01429.x (cited on page 87).

Kaplan, Steven N. and Per Stromberg (2001). "Venture capitals as principals: Contracting, screening, and monitoring". In: *American Economic Review* 91.2, pp. 426–430. DOI: 10.1257/aer.91.2.426 (cited on page 60).

Karney, Charles F. F. (2013). "Algorithms for geodesics". In: *Journal of Geodesy* 87.1, pp. 43–55. DOI: 10.1007/s00190-012-0578-z (cited on page 101).

Kempf, Alexander, Stefan Ruenzi, and Tanja Thiele (2009). "Employment risk, compensation incentives, and managerial risk taking: Evidence from the mutual fund industry". In: *Journal of Financial Economics* 92.1, pp. 92–108. DOI: 10.1016/j.jfineco.2008.05.001 (cited on pages 9, 15).

Khorana, Ajay (1996). “Top management turnover an empirical investigation of mutual fund managers”. In: *Journal of Financial Economics* 40.3, pp. 403–427. DOI: 10.1016/0304-405x(95)00852-6 (cited on page 15).

King, Timothy, Abhishek Srivastav, and Jonathan Williams (2016). “What’s in an education? Implications of CEO education for bank performance”. In: *Journal of Corporate Finance* 37, pp. 287–308. DOI: 10.1016/j.jcorpfin.2016.01.003 (cited on pages 84, 87).

Koenig, Lukas (2022). “Cut from the same Cloth: The Role of University Affiliations in Venture Capital Investments”. Working Paper available at SSRN. DOI: 10.2139/ssrn.4248420 (cited on pages 5, 83).

Koenig, Lukas and Hans-Peter Burghof (2022). “The Investment Style Drift Puzzle and Risk-Taking in Venture Capital”. In: *Review of Corporate Finance* 2.3, pp. 527–585. DOI: 10.1561/114.00000023 (cited on pages 4, 7, 117).

Koenig, Lukas and Julius Tennert (2022). “Tell me something new: startup valuations, information asymmetry, and the mitigating effect of informational updates”. In: *Venture Capital* 24.1, pp. 47–69. DOI: 10.1080/13691066.2022.2026744 (cited on pages 4, 57).

Köhn, Andreas (2018). “The determinants of startup valuation in the venture capital context: a systematic review and avenues for future research”. In: *Management Review Quarterly* 68.1, pp. 3–36. DOI: 10.1007/s11301-017-0131-5 (cited on page 72).

Kräussl, Roman and Stefan Krause (2014). “Has Europe Been Catching Up? An Industry Level Analysis of Venture Capital Success over 1985–2009”. In: *European Financial Management* 20.1, pp. 179–205. DOI: 10.1111/j.1468-036X.2013.12012.x (cited on page 17).

Kuhnen, Camelia M. (2009). “Business Networks, Corporate Governance, and Contracting in the Mutual Fund Industry”. In: *The Journal of Finance* 64.5, pp. 2185–2220. DOI: 10.1111/j.1540-6261.2009.01498.x (cited on pages 88, 110).

La Porta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert W. Vishny (1998). “Law and Finance”. In: *Journal of Political Economy* 106.6, pp. 1113–1155. DOI: 10.1086/250042 (cited on pages 19, 23, 46).

Lahr, Henry and Timothy E. Trombley (2020). “Early indicators of fundraising success by venture capital firms”. In: *Journal of Corporate Finance* 65, p. 101672. DOI: 10.1016/j.jcorpfin.2020.101672 (cited on page 16).

Laitinen, Erkki K. (2019). “Discounted Cash Flow (DCF) as a Measure of Startup Financial Success”. In: *Theoretical Economics Letters* Vol.09 No.08, p. 24. DOI: 10.4236/tel.2019.98185 (cited on page 65).

Leland, Hayne E. and David H. Pyle (1977). “Informational Asymmetries, Financial Structure, and Financial Intermediation”. In: *The Journal of Finance* 32.2, pp. 371–387. DOI: 10.2307/2326770 (cited on page 84).

Levenshtein, Vladimir Iosifovich (1966). “Binary codes capable of correcting deletions, insertions, and reversals”. In: *Soviet physics doklady*. Vol. 10. 8. Soviet Union, pp. 707–710 (cited on page 94).

Lewis, Virginia and Neil Churchill (1983). “The Five Stages of Small Business Growth”. In: *Harvard Business Review* 3 (cited on pages 58, 64).

Li, Haitao, Xiaoyan Zhang, and Rui Zhao (2011). “Investing in Talents: Manager Characteristics and Hedge Fund Performances”. In: *Journal of Financial and Quantitative Analysis* 46.1, pp. 59–82. DOI: 10.1017/s0022109010000748 (cited on pages 84, 87).

Li, Yong, Ilan B. Vertinsky, and Jing Li (2014). “National distances, international experience, and venture capital investment performance”. In: *Journal of Business Venturing* 29.4, pp. 471–489. DOI: 10.1016/j.jbusvent.2013.08.002 (cited on pages 19, 21, 121).

Ljungqvist, Alexander, Matthew Richardson, and Daniel Wolfenzon (2020). “The investment behavior of buyout funds: Theory and evidence”. In: *Financial Management* 49.1, pp. 3–32. DOI: 10.1111/fima.12264 (cited on pages 16, 17).

Megginson, William L. and Kathleen A. Weiss (1991). “Venture Capitalist Certification in Initial Public Offerings”. In: *The Journal of Finance* 46.3, pp. 879–903. DOI: 10.1111/j.1540-6261.1991.tb03770.x (cited on page 89).

Milgrom, Paul R. (1981). “Good News and Bad News: Representation Theorems and Applications”. In: *The Bell Journal of Economics* 12.2, pp. 380–391. DOI: 10.2307/3003562 (cited on page 60).

Miller, Danny, Xiaowei Xu, and Vikas Mehrotra (2015). “When is human capital a valuable resource? The performance effects of Ivy league selection among celebrated CEOs”. In: *Strategic Management Journal* 36.6, pp. 930–944. DOI: 10.1002/smj.2251 (cited on pages 84, 87).

Nahata, Rajarishi (2008). “Venture capital reputation and investment performance”. In: *Journal of Financial Economics* 90.2, pp. 127–151. DOI: 10.1016/j.jfineco.2007.11.008 (cited on pages 21, 73, 121).

Nahata, Rajarishi, Sonali Hazarika, and Kishore Tandon (2014). “Success in Global Venture Capital Investing: Do Institutional and Cultural Differences Matter?” In: *The Journal of Financial and Quantitative Analysis* 49.4, pp. 1039–1070. DOI: 10.1017/s0022109014000568 (cited on pages 12, 103).

Nanda, Ramana and Matthew Rhodes-Kropf (2013). “Investment cycles and startup innovation”. In: *Journal of Financial Economics* 110.2, pp. 403–418. DOI: 10.1016/j.jfineco.2013.07.001 (cited on page 16).

Nanda, Ramana, Sampsa Samila, and Olav Sorenson (2020). “The persistent effect of initial success: Evidence from venture capital”. In: *Journal of Financial Economics* 137.1, pp. 231–248. DOI: 10.1016/j.jfineco.2020.01.004 (cited on pages 19, 103, 124).

Neher, Darwin V (1999). "Staged financing: an agency perspective". In: *The Review of Economic Studies* 66.2, pp. 255–274. DOI: 10.1111/1467-937X.00087 (cited on page 59).

Norton, Edgar and Bernard H. Tenenbaum (1993). "Specialization versus diversification as a venture capital investment strategy". In: *Journal of Business Venturing* 8.5, pp. 431–442. DOI: 10.1016/0883-9026(93)90023-x (cited on page 12).

NVCA (2011). *National Venture Capital Association Yearbook 2011* (cited on page 1).

NVCA (2022). *National Venture Capital Association Yearbook 2022* (cited on pages 1, 2).

Pang, Bo and Lillian Lee (2008). "Opinion Mining and Sentiment Analysis". In: *Foundations and Trends in Information Retrieval* 2.1–2, pp. 1–135. DOI: 10.1561/1500000011 (cited on page 64).

Pintado, Tomás Ramón, Domingo García Pérez De lema, and Howard Van auken (2007). "Venture Capital in Spain by Stage of Development". In: *Journal of Small Business Management* 45.1, pp. 68–88. DOI: 10.1111/j.1540-627X.2007.00199.x (cited on page 65).

Podolny, Joel M. (1994). "Market Uncertainty and the Social Character of Economic Exchange". In: *Administrative Science Quarterly* 39.3, pp. 458–483. DOI: 10.2307/2393299 (cited on page 110).

Qaiser, Shahzad and Ramsha Ali (2018). "Text mining: use of TF-IDF to examine the relevance of words to documents". In: *International Journal of Computer Applications* 181.1, pp. 25–29. DOI: 10.5120/ijca2018917395 (cited on page 67).

Ramos, Juan (2003). "Using tf-idf to determine word relevance in document queries". In: *Proceedings of the first instructional conference on machine learning*. Vol. 242, pp. 29–48 (cited on page 67).

Renault, Thomas (2017). "Intraday online investor sentiment and return patterns in the U.S. stock market". In: *Journal of Banking & Finance* 84, pp. 25–40. DOI: 10.1016/j.jbankfin.2017.07.002 (cited on page 64).

Retterath, Andre and Reiner Braun (2020). "Benchmarking venture capital databases". Working Paper available at SSRN. DOI: 10.2139/ssrn.3706108 (cited on page 90).

Rin, Marco Da, Thomas Hellmann, and Manju Puri (2013). "Chapter 8 - A Survey of Venture Capital Research". In: ed. by George M. Constantinides, Milton Harris, and Rene M. Stulz. Vol. 2. Handbook of the Economics of Finance. Elsevier, pp. 573–648. DOI: https://doi.org/10.1016/B978-0-44-453594-8.00008-2 (cited on page 2).

Rosenstein, Joseph (1988). "The board and strategy: Venture capital and high technology". In: *Journal of Business Venturing* 3.2, pp. 159–170. DOI: 10.1016/0883-9026(88)90024-9 (cited on page 89).

Sahlman, William A. (1990). "The structure and governance of venture-capital organizations". In: *Journal of Financial Economics* 27.2, pp. 473–521. DOI: https://doi.org/10.1016/0304-405X(90)90065-8 (cited on pages 1, 2, 60).

Schertler, Andrea and Tereza Tykvová (2011). “Venture capital and internationalization”. In: *International Business Review* 20.4, pp. 423–439. DOI: 10.1016/j.ibusrev.2010.07.009 (cited on pages 21, 34).

Schwienbacher, Armin (2005). “An empirical analysis of venture capital exits in Europe and the United States”. EFA 2002 Berlin Meetings Discussion Paper available at SSRN. DOI: 10.2139/ssrn.302001 (cited on page 17).

Seibert, Scott E., Maria L. Kraimer, and Robert C. Liden (2001). “A Social Capital Theory of Career Success”. In: *Academy of Management Journal* 44.2, pp. 219–237. DOI: 10.2307/3069452 (cited on page 86).

Shane, Scott and Toby Stuart (2002). “Organizational Endowments and the Performance of University Start-ups”. In: *Management Science* 48.1, pp. 154–170. DOI: 10.1287/mnsc.48.1.154.14280 (cited on page 58).

Shepherd, Dean A and Andrew Zacharakis (2001). “The venture capitalist-entrepreneur relationship: control, trust and confidence in co-operative behaviour”. In: *Venture Capital: an international journal of entrepreneurial finance* 3.2, pp. 129–149. DOI: 10.1080/13691060110042763 (cited on page 59).

Sievers, Soenke, Christopher F Mokwa, and Georg Keienburg (2013). “The relevance of financial versus non-financial information for the valuation of venture capital-backed firms”. In: *European Accounting Review* 22.3, pp. 467–511. DOI: 10.1080/09638180.2012.741051 (cited on page 59).

Sørenson, Morten (2007). “How Smart Is Smart Money? A Two-Sided Matching Model of Venture Capital”. In: *The Journal of Finance* 62.6, pp. 2725–2762. DOI: 10.1111/j.1540-6261.2007.01291.x (cited on page 103).

Sørenson, Morten (2008). “Learning by Investing: Evidence from Venture Capital”. SIFR Research Report Series. AFA 2008 New Orleans Meetings Paper. DOI: 10.2139/ssrn.967822 (cited on page 12).

Sunesson, Daniel (2009). “Alma mater matters: the value of school ties in the venture capital industry”. In: *Available at SSRN 1372463*. Working Paper available at SSRN. DOI: 10.2139/ssrn.1372463 (cited on pages 85, 91).

Tetlock, Paul C. (2007). “Giving Content to Investor Sentiment: The Role of Media in the Stock Market”. In: *The Journal of Finance* 62.3, pp. 1139–1168. DOI: 10.1111/j.1540-6261.2007.01232.x (cited on page 64).

Tian, Xuan (2012). “The Role of Venture Capital Syndication in Value Creation for Entrepreneurial Firms”. In: *Review of Finance* 16.1, pp. 245–283. DOI: 10.1093/rof/rfr019 (cited on page 121).

Tumasjan, Andranik, Reiner Braun, and Barbara Stolz (2021). “Twitter sentiment as a weak signal in venture capital financing”. In: *Journal of Business Venturing* 36.2, p. 106062. DOI: 10.1016/j.jbusvent.2020.106062 (cited on page 64).

Tykvová, Tereza (2018a). "Legal framework quality and success of (different types of) venture capital investments". In: *Journal of Banking & Finance* 87, pp. 333–350. DOI: 10.1016/j.jbankfin.2017.10.015 (cited on pages 40, 46).

Tykvová, Tereza (2018b). "Venture capital and private equity financing: an overview of recent literature and an agenda for future research". In: *Journal of Business Economics* 88.3-4, pp. 325–362. DOI: 10.1007/s11573-017-0874-4 (cited on page 2).

Tykvová, Tereza and Andrea Schertler (2014). "Does Syndication With Local Venture Capitalists Moderate the Effects of Geographical and Institutional Distance?" In: *Journal of International Management* 20.4, pp. 406–420. DOI: 10.1016/j.intman.2014.09.001 (cited on pages 11, 21, 103, 121).

Verrecchia, Robert E. (1983). "Discretionary disclosure". In: *Journal of Accounting and Economics* 5, pp. 179–194. DOI: 10.1016/0165-4101(83)90011-3 (cited on page 61).

Wang, Susheng and Hailan Zhou (2004). "Staged financing in venture capital: moral hazard and risks". In: *Journal of Corporate Finance* 10.1, pp. 131–155. DOI: 10.1016/S0929-1199(02)00045-7 (cited on pages 59, 60).

Wermers, Russ (2012). "Matter of style: The causes and consequences of style drift in institutional portfolios". CFR Working Papers. Working Paper available at SSRN. DOI: 10.2139/ssrn.2024259 (cited on page 8).

Wong, S. K. M. and Y. Y. Yao (1992). "An information-theoretic measure of term specificity". In: *Journal of the American Society for Information Science* 43.1, pp. 54–61. DOI: 10.1002/(SICI)1097-4571(199201)43:1<54::AID-ASI5>3.0.CO;2-A (cited on page 67).

List of Figures

1.1 Global Venture Capital Investment into Portfolio Companies (2004-2021) . 2
1.2 Graphical Structure of this Thesis 3

4.1 Graphical Sample Overview of Locations of VC firms and startups 92

List of Tables

2.1 Overview and Definition of Main Variables of Interest for Deal-Level Analysis 23
2.2 Overview and Definition of Main Variables of Interest for Fund-Level Analysis 24
2.3 Sample Composition and Descriptive Statistics at Deal-Level 28
2.4 Sample Composition and Descriptive Statistics at Fund Level 30
2.5 Descriptive Statistics and Mean Comparison of Style Drift Determinants . 32
2.6 Correlation Matrix of Variables in the Style Drift Determinants Analysis . 33
2.7 Determinants of Stage Drifts 37
2.8 Determinants of Location Drifts 39
2.9 Determinants of Industry Drifts 42
2.10 Relationship of Uncertainty Avoidance and Style Drifts 45
2.11 Effect of Style Drifts on Individual Investment Success 47
2.12 Effect of Style Drifts on Individual Investment Success Controlling for Endogeneity 49
2.13 Effect of Style Drifts on Overall Fund Investment Success 52

3.1 Text Analysis Methodology Overview: Polarity and Specificity Approach . 66
3.2 Overview and Definition of Main Variables of Interest 69
3.3 Sample Overview and Descriptive Statistics 71
3.4 Basic Regressions Analyzing Information Content 74
3.5 Regressions Analyzing Role of Information Specificity 77
3.6 Regressions Analyzing Moderating Effect of the Level of Information Asymmetry 78

4.1 Summary of the Sample Scope 93
4.2 University Affiliations of Founders and Investors 95
4.3 Matches between startups and VC firms and shared university affiliations . 100
4.4 Overview and Definition of Variables of the Analysis 102
4.5 The Effect of Individual Educational Background on Investment 105
4.6 The Effect of a Shared Educational Background on Investment 107
4.7 The Effect of Redundant and Exclusive Educational Ties on Investment . . 109

4.8 Robustness Checks for the effect of Shared Educational Background on Investment . . . 112
4.9 Scope: The Effect of a Shared Educational Background on Acting as Lead Investor . . . 115
4.10 The Effect of a Shared Educational Background on Taking a Board Seat . 116
4.11 Scope: The Effect of a Shared Educational Background on the Number of Rounds . . . 118
4.12 Timing: The Effect of a Shared Educational Background on Investing in the First Round . . . 120
4.13 Timing: The Relationship between Shared Educational Background and Startup Age . . . 122
4.14 Success: The Relationship between Educational Background and Exit Outcome 123

A

Appendix

- Declarations of Co-Authorship
- Curriculum Vitae
- Eidesstattliche Versicherung

A.1 Declarations of Co-Authorship

UNIVERSITÄT
HOHENHEIM

KO-AUTORENERKLÄRUNG *DECLARATION OF CO-AUTHORSHIP*

(Für kumulative Dissertationen)

Name des Kandidaten: (*Name of the candidate*): Lukas König

Titel des Artikels (*Title of the article*):

The Investment Style Drift Puzzle and Risk-Taking in Venture Capital

☐ nicht eingereicht (*not submitted*)

☐ eingereicht bei (*submitted to*):

☒ Zur Veröffentlichung angenommen oder veröffentlicht in (*accepted for publication or published in*):

Review of Corporate Finance

Arbeitsanteil des Kandidaten an vorgenanntem Artikel *Quantification of candidates contribution to the article (overall)*:

☐ hat zur Arbeit beigetragen/has contributed to the work (<1/3)

☐ hat wesentlich zur Arbeit beigetragen/has made a substantial contribution (1/3 to 2/3)

☐ hat einen Großteil der Arbeit allein erledigt/did the majority of the work independently (>2/3)

☒ federführender Autor/lead author

Ko-Autoren *Co-authors* (Name und Kontaktdaten/*full name; contact*):

1. Hans-Peter Burghof, Chair of Banking and Financial Services, Universität Hohenheim, Schloss Osthof-Nord, 70599 Stuttgart, burghof@uni-hohenheim.de
2.
3.
4.

Hiermit bestätige ich die Richtigkeit des oben beschriebenen Arbeitsanteils des Kandidaten.
I hereby confirm the candidate's contribution as quantified above.

Stuttgart 4.10.2022

Ort, Datum *Place, Date*

Unterschrift Ko-Autor *Signature Co-author*

Stand 02/2019. Alle personenbezogenen Angaben gelten stets für Frauen und Männer gleichermaßen. 1 I 1

UNIVERSITÄT HOHENHEIM

KO-AUTORENERKLÄRUNG *DECLARATION OF CO-AUTHORSHIP*

(Für kumulative Dissertationen)

Name des Kandidaten: (*Name of the candidate*)

Lukas König

Titel des Artikels (*Title of the article*):

Tell me something new: startup valuations, information asymmetry, and the mitigating effect of informational updates

☐ nicht eingereicht (*not submitted*)

☐ eingereicht bei (*submitted to*):

☒ Zur Veröffentlichung angenommen oder veröffentlicht in (*accepted for publication or published in*):

Venture Capital

Arbeitsanteil des Kandidaten an vorgenanntem Artikel *Quantification of candidates contribution to the article (overall)***:**

☐ hat zur Arbeit beigetragen/has contributed to the work (<1/3)

☐ hat wesentlich zur Arbeit beigetragen/has made a substantial contribution (1/3 to 2/3)

☐ hat einen Großteil der Arbeit allein erledigt/did the majority of the work independently (>2/3)

☒ federführender Autor/lead author

Ko-Autoren *Co-authors* (Name und Kontaktdaten/*full name; contact*):

1. Julius Tennert, Chair of Banking and Financial Services, Universität Hohenheim, Schloss Osthof-Nord, 70599 Stuttgart
2.
3.
4.

Hiermit bestätige ich die Richtigkeit des oben beschriebenen Arbeitsanteils des Kandidaten.

I hereby confirm the candidate's contribution as quantified above.

Karlsruhe, 01.10.2022

Ort, Datum *Place, Date*

Unterschrift Ko-Autor *Signature Co-author*

Stand 02/2019. Alle personenbezogenen Angaben gelten stets für Frauen und Männer gleichermaßen. 1 I 1

A.2 Curriculum Vitae

Lukas M. **König**

M.Sc. Financial Management

03.09.1991 | Lerchenstr. 24, 70176 Stuttgart | +49 152 06042234 | lukaskoeni@gmail.com | lukas-koenig

I am a sharp mind with a passion for technology combining strong analytical skills with emotional intelligence.

Experience

Senior Consultant — *Stuttgart, Germany*
Mercedes-Benz Management Consulting | Strategy Consulting — *Apr. 2021 - today*

- Headed autonomous driving stragegy work package for the overall Mercedes software strategy; developed a holistic autonomous driving strategy framework; conducted C-level strategy workshops
- Developed a wholistic semiconductor strategy to ensure supply chain resilience and future technological competitiveness for SoCs
- Kickstarted strategic project lead for MB.OS (Mercedes-Benz Operating System); developed demand management process and steering model for new customer functions
- Defined new organizational setup for all eDrive activities; bundled eDrive activities in a center of competence across organizational units

MOVE Performance Associate — *Stuttgart, Germany*
Mercedes-Benz AG | Mercedes-Benz Transformation — *Dec. 2019 - Mar. 2021*

- Set up a major finance and strategy transformation project for Mercedes-Benz with the ambition of multi-billions of annual savings and 20 individual work packages; headed central Marketing & Sales and Operations work streams; supported preparation of a restructuring plan
- Worked on a headcount reduction project with the goal to increase efficiency by 25% in the operations-finance departments; conducted analyses to identify efficiency potential; moderated workshops with the leadership team to decide efficiency measures

Financial Business Development Associate — *Stuttgart, Germany*
Daimler AG | Finance Transformation — *Jan. 2018 - Nov. 2019*

- Coordinated cross-functional-expert autonomous driving strategy swarm; conducted financial evaluation of business model options and analyzed corporate autonomous driving strategy space leading to shift of funding of 700mn€ from the cars to the trucks division
- Prepared and conducted multiple workshops with divisional CFO; created corporate board-level management documents
- Developed next level autonomous mobility-as-a-service market simulation model including substitution effects of Mercedes sales
- Conceptualized and implemented an end-to-end financial simulation model; conducted analysis of financial impact of disruptive 'CASE' trends on Mercedes-Benz's bottom line with Bloomberg's BNEF platform; established cutting-edge driver-based business intelligence tool
- Worked on steering-model for new and emerging business models outside the classical car business
- Recruited, supervised, and trained three interns; oversaw, supported and advised two bachelor and one master thesis-projects

Teaching and Research Assistant — *Hohenheim, Germany*
University of Hohenheim | Chair of Banking and Financial Services — *May. 2017 - Jan. 2018*

- Conducted research for PhD candidates supporting the publication of two research papers in the field of sentiment based forecasts; worked with corporate finance databases and large financial data-sets in the area of cryptocurrencies; programmed statistical models in Stata
- Proposed curriculum and realized concept for Trading & Exchanges class teaching 40 master level students on modern capital markets and investments; held tutorials and office hours for Fundamentals in Corporate Finance class for over 800 bachelor students

Working Student - Partnerships and Marketing — *Stuttgart, Germany*
SWS GmbH — *Oct. 2015 - Jul. 2016*

- Supported business case of an e-mobility scooter sharing project leading to the launch of a pilot within 3 months; contributed to cooperation strategy and supported partnership selection for rollout; coordinated service providers for operative marketing projects

Working Student - Controlling — *Schwieberdingen, Germany*
Robert Bosch GmbH — *Mar. 2015 - Aug. 2015*

- Supported lean management project; identified process efficiency potentials; supported FP&A team at months-end reporting

Internship - International Purchasing and Bachelor - Thesis Clean Energy Systems — *Bietigheim-Bissingen, Germany*
Dürr Systems GmbH — *Mar. 2014 - Mar. 2015*

- Analyzed market environment and competition for a microturbine product launch; proposed a marketing strategy and piloted measures for strategy implementation; coordinated local purchasers for plant engineering projects in China and Mexico overseeing a 600mn € budget

Education

Dr. oec. Banking and Financial Services — *Hohenheim, Germany*
University of Hohenheim — *2020 - 2023*
PhD Thesis Title: Empirical Essays on Agency Problems in Venture Capital

International Winter School — *St. Gallen, Switzerland*
University of St.Gallen — *2021*
PhD course: Text Mining with R as part of the Global School in Empirical Research Methods (GSERM)

M.Sc. Financial Management (Grade: 1.3 | Top of class) — *Hohenheim, Germany*
University of Hohenheim — *2015 - 2018*
Thesis: The other side of the coin: An empirical analysis of the dynamic relationships between cryptocurrency prices and their determinants

Lukas M. König · Résumé 1/2

Education (continued)

Academic Exchange Program — *Long Beach, California*
CALIFORNIA STATE UNIVERSITY LONG BEACH — *2016 - 2017*
One academic year as an international exchange student in the Study Abroad @ The Beach program

B.Eng. Engineering Management (Grade 1.1 | Top of class) — *Esslingen, Germany*
ESSLINGEN UNIVERSITY — *2012 - 2015*
Thesis: Business Development im B2B-Markt: Entwicklung einer Marketingkonzeption am Beispiel Dürr EcoEnergy CPS

Scholarships & Awards

2019	**Best master thesis**, Bundesverband Alternative Investments e.V.	*Award*
2018	**Best graduate of the management program (Top 1 of 254)**, University of Hohenheim	*Award*
2017	**Dean's List (best 3% of students)**, University of Hohenheim	*Award*
2017	**Deutschlandstipendium**, BBBank eG	*Scholarship*
2016	**Dean's List (best 3% of students)**, University of Hohenheim	*Award*
2016	**Baden-Württemberg Stipendium**, Baden-Württemberg Stiftung	*Scholarship*
2015	**Deutschlandstipendium**, Karl Schlecht Stiftung	*Scholarship*
2015	**Best student of the program (Top 1 of 79)**, Esslingen University Alumni Association	*Award*

Skills

Programming Languages Python (focus on Pandas and other Data Science related libraries), R, Stata, SQL, Swift, LaTeX, C

Software

advanced Microsoft Office (PowerPoint, Excel incl. VBA, Word), ValSight

basics PowerBI, Tableau, Jira, Kanbo, Asana

Languages German (*native*), English (*fluent*), Spanish (*basics*)

Stuttgart, 14.01.2023

Place, Date

Lukas König

A.3 Eidesstattliche Versicherung

Anlage 3

Eidesstattliche Versicherung über die eigenständig erbrachte Leistung

gemäß § 18 Absatz 3 Satz 5 der Promotionsordnung der Universität Hohenheim für die Fakultäten Agrar-, Natur- sowie Wirtschafts- und Sozialwissenschaften

1. Bei der eingereichten Dissertation zum Thema

Empirical Essays on Agency Problems in Venture Capital

…………………………………………………………………………………………...

handelt es sich um meine eigenständig erbrachte Leistung.

2. Ich habe nur die angegebenen Quellen und Hilfsmittel benutzt und mich keiner unzulässigen Hilfe Dritter bedient. Insbesondere habe ich wörtlich oder sinngemäß aus anderen Werken übernommene Inhalte als solche kenntlich gemacht.

3. Ich habe nicht die Hilfe einer kommerziellen Promotionsvermittlung oder -beratung in Anspruch genommen.

4. Die Bedeutung der eidesstattlichen Versicherung und der strafrechtlichen Folgen einer unrichtigen oder unvollständigen eidesstattlichen Versicherung sind mir bekannt.

Die Richtigkeit der vorstehenden Erklärung bestätige ich. Ich versichere an Eides Statt, dass ich nach bestem Wissen die reine Wahrheit erklärt und nichts verschwiegen habe.

Stuttgart, 14.01.2023

Ort, Datum

Unterschrift